ESSAYS ON URBAN STRUCTURE AND DYNAMICS

by

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Abstract

This thesis consists of three essays on urban structure and dynamics. These essays use empirical tools from empirical industrial organization and applied microeconomics to examine how cities grow and change.

Access to high-quality local services constitutes an important amenity in residents’ valuation of cities. In “Industry dynamics and the value of variety in nightlife: evidence from Chicago”, I examine consumer preferences for variety in nightlife to understand these preferences and their impact on nightlife industry dynamics. I develop a structural dynamic model for venue entry and exit in the nightlife industry and estimate the model using a panel of liquor license data from Chicago. I find strong preferences for variety. My results suggest that in equilibrium a new entrant can increase profits for incumbent venues in some cases due to increased demand. However, potential entrants face high barriers to entry.

In “Land value gradients and the level and growth of housing prices”, coauthor Tom Davidoff and I ask whether urban land rent gradients affect the level and growth of housing rents and prices. We use residential rents and the location of Starbucks stores to proxy for land prices, and calculate a gradient measure that allows for multiple peaks of land rent within a metropolitan area. Our measures of land rent gradients are significantly associated with high and rising prices, and explain some of the cross-sectional variation in prices. However, our measure does not explain the abnormally high rent and prices in Pacific and Northeastern coastal “Superstar Cities.”

Bartik shocks are widely used as an instrument for local labour demand. A potential concern with this instrument is potential endogeneity in the presence of correlation between city-level industrial composition and the outcome variable of interest. In “A control function approach to the correlated components of Bartik shocks”, I formalize this endogeneity concern and introduce a control function correction that, given additional assumptions, addresses the potential endogeneity. I demonstrate the application of this novel approach by estimating a housing supply function.
Preface

“Industry dynamics and the value of variety in nightlife: evidence from Chicago” is based on my job market paper. In the preparation of this chapter I identified the economic question, collected the data, developed the theoretical model, estimated the parameters of the model, and interpreted the economic significance of the results. This chapter has benefited from insightful comments and criticism from my committee members as well as seminar participants.

“Land value gradients and the level and growth of housing prices” is a collaborative project with Dr. Tom Davidoff of my supervisory committee. For this chapter, I collected the data, developed the novel estimator for the gradient, and performed most of the empirical estimation. Dr. Davidoff identified the primary research question, situated our results in the context of the urban economics literature, and performed a share of the empirical estimation.

For “A control function approach to the correlated components of Bartik shocks”, I identified the economic question, developed the theoretical model in close consultation with my committee members, estimated the parameters of the model, and interpreted the economic significance of the results. This chapter was developed under the supervision of my committee and has benefited from their comments.
Table of Contents

Abstract ................................................................. ii

Preface ................................................................. iii

Table of Contents ..................................................... iv

List of Tables ............................................................ vii

List of Figures .......................................................... x

Acknowledgements ..................................................... xii

1 Introduction ............................................................ 1

2 Industry dynamics and the value of variety in nightlife: evidence from
   Chicago ............................................................... 5
   2.1 Introduction ....................................................... 5
   2.2 Model .............................................................. 9
       2.2.1 Static model .................................................. 11
       2.2.2 Dynamic model ............................................. 16
       2.2.3 Estimation strategy ....................................... 20
       2.2.4 Identification of colocaiton benefits .................. 24
   2.3 Data and industry details ...................................... 26
       2.3.1 Nightlife venues .......................................... 26
       2.3.2 Neighbourhoods ........................................... 30
       2.3.3 Regulatory environment .................................... 33
Appendices ................................................................. 107
A Proof of Proposition 1 ................................................. 107
B Proof of Proposition 2 ................................................. 111
C Venue category verification ........................................... 112
D Maximum likelihood estimation results ......................... 114
List of Tables

2.1 Summary statistics for the venues in the sample. Standard deviation for duration in parentheses. ............................................................... 29

2.2 Likelihood ratio tests for Cox proportional hazard survival models of venue entry and exit. The first column adds controls for the number of venues of each type in the same neighbourhood. The second column adds controls for the number of venues of each type in neighbouring neighbourhoods (weighted by the length of shared border between neighbourhoods). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. ............... 32

2.3 Summary statistics for the 77 neighbourhoods in the sample. The last two rows are regulatory variables which are not included in the principal component analysis but rather included directly. ................................. 36

2.4 Factor loadings for principal component analysis together with the cumulative share of variance explained by the principal components. ....................... 37

2.5 Maximum likelihood estimation results for the CES parameters \( \eta \) and \( \rho \). Standard errors in parentheses. .............................................. 37

2.6 Maximum likelihood estimation results for the move arrival rate parameters \( \alpha \) and \( \lambda \). All values are measured in \( 10^{-3} \) days\(^{-1} \). Standard errors in parentheses. ............................................................... 40

2.7 Maximum likelihood estimation results for the logarithm of deterministic component of the sunk cost of entry and the exit payoff. The “baseline” entry cost reflects the entry cost in the absence of local regulation. Standard errors in parentheses. ......................................................... 42

2.8 Estimated sunk cost of entry. 95% confidence intervals in parentheses. . .. 44
2.9 Proportion of observations where a new entry would increase the profit of incumbent venues. The column variable is the type of the entrant while the row variable is the type whose change in profit is shown. All values are expressed in percentage of observations. 95% confidence intervals in parentheses.

2.10 Maximum likelihood estimation results for the CES parameters $\eta$ and $\rho_{\ell}$ with clustered neighbourhoods of varying sizes. Table 2.5 shows the corresponding baseline elasticity values. Standard errors in parentheses.

2.11 Maximum likelihood estimation results for the CES parameters $\eta$ and $\rho_{\ell}$ under estimation matching only the entry rate and only the exit rate. Table 2.5 shows the corresponding baseline elasticity values. Standard errors in parentheses.

2.12 Maximum likelihood estimation results for the parameters $A$, $B$, and $C$ from the profit function specification in Equation 2.19. For legibility, all values are scaled up by a factor of $10^3$. Standard errors in parentheses.


3.2 Summary statistics for the Craigslist rent location data. Throughout, the unit of observation is the MSA.

3.3 Summary statistics for the Zillow price data and the rent-price ratio from the Zillow price and Craigslist rent data. Throughout, the unit of observation is the MSA.

3.4 Summary statistics for additional control variables.

3.5 Correlations between supply inelasticity factors. Throughout, the unit of observation is the metropolitan area.

3.6 Regression results for the current rent without the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

3.7 Regression results for current rent with the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
3.8 Regression results for the price-rent ratio without the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. .......................................................... 75

3.9 Regression results for the price-rent ratio with the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. .......................................................... 76

3.10 Regression results for the long-term price growth without the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. .......................................................... 77

3.11 Regression results for the long-term price growth with the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. .......................................................... 78

4.1 Regression results for the housing supply curve at the MSA level. For legibility, the control function coefficient and its standard errors are scaled by a factor of $10^3$. Standard errors in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%. .......................................................... 89

C1 Results of a multinomial logit regression of the licensing categories on the most frequently-assigned Yelp categories. The regression sample is the set of venues which matched with Yelp businesses. The omitted licensing category is the “Amusement only” category. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. .......................... 113

D1 Maximum likelihood estimation results for all parameters. If the variable name includes “Log”, I estimate the logarithm of the corresponding model parameter. Standard errors in parentheses. .......................... 118
List of Figures

2.1 Profit by sector in a two-sector example. ........................................... 15
2.2 Consumer in a two-sector example. Figure 2.1 shows the corresponding venue
profit. ........................................................................................................... 17
2.3 Geographical distribution of venues within Chicago. ............................... 28
2.4 Distribution of venues’ durations within the sample. ............................... 29
2.5 Comparison of variation in nearest-neighbour differences within and between
neighbourhoods. The abbreviation “N.s.d” refers to the normalized standard
development — that is, the standard deviation divided by the mean. The ab-
breivation “n.n” refers to the nearest neighbour. Each label $k$ denotes the
normalized standard deviation for the distance to the $k^{th}$ nearest neighbour.
This figure only includes venues in the sample at the end of the sample period.
However, results are similar at other points in the sample period. ............ 31
2.6 Neighbourhood attributes. ................................................................. 38
2.7 First-stage results for venue entry and exit rates as a function of state. Units
are days$^{-1}$ throughout. Error bars in grey represent one standard deviation. 39
2.8 Observed and predicted wait times between state transitions (i.e., venue entry
or exit). Each point represents a single $(n,d,r)$ state. ............................... 46
2.9 Changes to consumer welfare from one additional venue of each type. All
changes expressed as a percentage of the baseline welfare. ...................... 48
2.10 Changes to entry probability from lower entry cost. All changes expressed as
the change in the rate of new entrants choosing to enter the market per year. 51
2.11 Changes to entry probability from laissez-faire local regulation. All changes expressed as the change in the rate of new entrants choosing to enter the market per year. Results for venues in the “Amusement only” category are not shown as venues without liquor licenses do not face local liquor regulation and the indirect effect from other venues’ higher entry rate is very small.  
2.12 Map of clustered neighbourhoods generated using clustering radius $d = 500m$. 

3.1 Spatial distribution of Starbucks locations in four sample cities.  
3.2 Spatial distribution of one-bedroom apartments in four sample cities, together with monthly rent.  
3.3 Comparison of rent gradient and Starbucks density gradient for metropolitan areas in the sample. Metropolitan areas with a population greater than three million are labelled by their principal cities.
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1 Introduction

Cities have become the dominant environment for human life. As of 2014, 54% of world population and 82% of the Canadian population live in cities (United Nations, Department of Economic and Social Affairs, Population Division, 2014). The economic benefits of many people living and working near enough to exchange specialized goods and services were identified early in the classical economic literature\(^1\) and modern researchers have found that the interactions of firms and residents within cities are play an important role in providing a high standard of living for their residents (Fujita and Thisse, 2002; Rosenthal and Strange, 2004; Glaeser and Gottlieb, 2009). Accordingly, understanding the processes which drive the development and evolution of cities is essential to social scientists and policymakers seeking to improve their residents’ well-being.

The body of this thesis comprises three studies in urban economics which address the structure and dynamics of cities. In these studies, I build on innovative techniques from empirical microeconometrics and industrial organization. I use data sets that describe interactions and dynamics within cities to address questions of how cities grow and change. These studies are linked by their use of empirical evidence to describe the interactions between firms and resident within cities and understand the role of these interactions in cities’ structures and dynamics. The first investigates firm dynamics among different types of nightlife venues, the second introduces a new measure of firms’ and residents’ willingness to substitute across locations within a city, and the third develops a new empirical technique for understanding how changes to local labour demand impact housing prices and other city-level outcomes.

“Industry dynamics and the value of variety in nightlife: evidence from Chicago” studies the dynamics of the nightlife industry. In particular, this paper focuses on consumers preferences for variety both within and between types of nightlife venue and the role of these

\(^1\)In particular, Ibn Khaldun (1377) and Smith (1776) note the increased scope for specialized labour within cities while Marshall (1890) identifies productivity gains between firms sharing common suppliers and workers learning skills from each other.
preferences in venues’ decisions to enter and exit the market. This paper contributes to the literature that attempts to understand firms’ locational decisions by developing models that relate firms’ behaviour to firms’ underlying costs and constraints and consumers’ underlying preferences (Davis, 2006; Jia, 2008; Dunne et al., 2013). It is the first paper in this literature to examine the interactions between closely related industries by considering consumers preferences across different types of nightlife venues.

I develop and estimate a structural model of nightlife venues’ entry and exit decisions. This model predicts venues’ entry and exit decisions as a function of the number of nearby venues of similar and different types, the stringency of neighbourhood-level nightlife regulation, and the underlying structural parameters of consumers’ behaviour and venues’ costs. The model is forward-looking — that is, venues make their entry and exit decisions in response to each others’ predicted entry and exit decisions. I estimate this model using a continuous-time methodology introduced in Arcidiacono et al. (2012) that allows for computationally tractable estimation of a model with multiple interacting venue types.

My results suggest that consumers have very strong preferences for variety between nightlife venues. In fact, these preferences are sufficiently strong that in many observations my model predicts a counterfactual new venue would increase profits for nearby incumbents as the added enjoyment of nightlife would lead to more residents going out and consuming nightlife. The results indicate that these spillovers are present both within and between different types of nightlife venue. As well, I find that nightlife venues face very high barriers to entry. These barriers can partially be attributed to local regulation but also largely reflect the high nonregulatory costs of opening a new venue. In additional to their relevance to the literature on firms’ locational preferences, these results provide some indication of how consumer amenities develop within cities; research has shown that these amenities are important in determining residents’ migration decisions (Rappaport, 2008; Lee, 2010; Albouy et al., 2013). As well, because this study focuses on the nightlife industry, the results provide an empirical contribution to the policy discussion of how cities can chose local policies that promote or restrict nightlife in different neighbourhoods according to residents’ preferences (Heath, 1997; Campo and Ryan, 2008; Darchen, 2013a).

“Land value gradients and the level and growth of housing prices” develops a new mea-
sures of residents’ and firms’ willingness to substitute between neighbourhoods within a city. This paper contributes to an active strain of literature that attempts to use differences in cities’ housing demand growth or housing supply constraints to explain cross-city differences in housing price growth (Mian and Sufi, 2009; Huang and Tang, 2012; Davidoff, 2013a). Of particular interest to the economic literature is the consistently faster price growth in a few coastal cities, which are closely related to the “Superstar Cities” described in Gyourko, Mayer and Sinai (2013). Davidoff (2015) finds that the existing measures of cross-city differences cannot explain these cities’ housing markets’ disparate performance compared to other cities.

Coauthor Tom Davidoff and I introduce and calculate a measure of this willingness to substitute between neighbourhoods. The measure is based on the spatial rate of change of land value within a city. Cities with steeper changes in land value are associated with a lower willingness to substitute within the city. We show that these measures correlate closely with other measures of supply elasticity within cities (including the measures introduced by Gyourko, Saiz and Summers (2008) and Saiz (2010)). Moreover, our measure plays a significant role in explaining cross-city differences in housing rents as well as short-term and long-term price growth. However, even when taken together, our new measure and the prevalent measures of demand growth and supply constraints cannot explain why the coastal cities’ housing markets consistently outperform the rest of the country. These results contribute useful information to the understanding of cross-city differences in housing markets.

“A control function approach to the correlated components of Bartik shocks” introduces a new technique that builds on research tools widely used in the urban economics literature. Bartik (1991) and Blanchard and Katz (1992) introduced the “Bartik shock” instrument variable, which is intended to provide a source of variation to labour demand that is driven by macroeconomic trends and therefore uncorrelated with the particular conditions of a given city. This purpose of this instrumental variable is to provide a source of variation to city-level outcomes such as housing prices (Saiz, 2010; Paciorek, 2013) and migration (Partridge et al., 2012; Guerrieri, Hartley and Hurst, 2013) decisions that allow researchers to identify the causal impact of shifts in labour demand on these outcomes. As discussed in
Baum-Snow and Ferreira (2014), the Bartik shock instrument is widely used in the economic literature.

In this study, I discuss concerns regarding the Bartik shock’s correlation with the industrial composition of the local workforce. I show that the use of the Bartik shock as an instrumental variable implicitly assumes that the city’s industrial composition has no relationship with the outcome variable of interest except through its impact on labour demand. In many situations, this assumption is possibly unwarranted; local industrial composition can interact with amenities, local regulation, population change, and other conditions in many complicated ways. I develop a theoretical framework that accounts for this potential correlation and propose an adjusted estimation technique that can potentially account for this correlation. This adjustment is novel to the economic literature. Its use may account for correlation between a city’s industrial composition and other processes within the city that are important in understanding how cities adjust to changing labour demand.

These studies incorporate the close relationships within the spatially concentrated economic activity that defines cities and provide empirical results that contribute to our understanding of how cities grow and change. Taken together, they demonstrate the importance of understanding the interactions and processes within cities to studying and improving the lives of their residents.
2 Industry dynamics and the value of variety in nightlife: evidence from Chicago

2.1 Introduction

Consumer access to city-specific non-tradeable goods and services plays an integral role in the growth and development of cities. Glaeser, Kolko and Saiz (2001) suggest that the welfare gain from these consumption amenities in cities is an increasingly important factor in overall urban growth and an active literature has indicated the importance of consumption amenities to urban migration decisions (Rappaport, 2008; Lee, 2010; Albouy et al., 2013). The value of amenities to urban quality of life is also recognized outside of the urban economics literature. For example, Bloomberg Businessweek includes restaurants, bars, libraries, museums, professional sports teams, and park space in its annual ranking of “America’s 50 Best Cities” and Livability.com explicitly includes entertainment and cultural amenities in its “Top 100 Places to Live” rankings.

In this study, I focus on bars, clubs, pool halls, arcades, bowling alleys, and other private businesses which exist primarily to facilitate social interactions in an informal setting. (Throughout, I use the terms “nightlife venues” and “nightlife industry” to describe these businesses.) I estimate a structural model of the nightlife industry with panel data on venue entry and exit to investigate consumer preference for access to variety in nightlife venues. The structural model allows me to assess the impact of consumers’ preference for variety on venue profit as well as venue entry and exit.

Nightlife has been recognized in the sociology literature (Farrer, 2008; Chew, 2009; Grazian, 2009) and in the urban policy literature (Heath, 1997; Campo and Ryan, 2008; Darchen, 2013a) as a particularly important amenity in shaping residents’ views of cities. Peters and Lakomski (2010) directly connect vibrant nightlife to attracting “a creative class of talented professionals” and Dewan (2005) describes a “hipness battle” between US cities,
including an effort in Lansing, Michigan under the “Cool Cities Initiative” to make the city more attractive to young professionals by providing shuttle buses between bars\(^1\). Many cities have enacted policies to encourage the development of nightlife, including several large centres in Britain (Heath, 1997), smaller cities in Indiana (Faulk, 2006), and rapidly growing cities such Guangzhou in China (Zeng, 2009).

Vibrant nightlife is closely associated with access to a variety of nightlife venues. Currid (2007) notes that a dense concentration of nightlife venues is more appealing to consumers than spatially isolated venues. As one lounge manager stated of a dense nightlife district in Philadelphia, “It gives you variety. You don’t want to go to the same place” (Harris, 2003). Picone, Ridley and Zandbergen (2009) attribute this to a consumer preference for “bar-hopping” (that is, a preference for visiting many venues in one night). However, some consumers may instead prefer access to different venues on each night; in the context of nightclub design, Kaiser, Ekblad and Broling (2007) discuss the difficulty of simultaneously addressing the preferences of bar-hopping patrons and patrons who spend the entire night at a single venue. In both cases, understanding consumer preferences for variety in nightlife is essential to understanding the development and valuation of nightlife amenities.

An emerging economic literature studies consumer valuation of consumption amenities and particularly consumer preference for access to variety. These papers generally follow the framework for consumer preference for variety established by Feenstra (1994). Among others, Broda and Weinstein (2006) infer consumer preferences for variety in goods from trade data, Li (2012) and Handbury and Weinstein (2011) study gains from variety using evidence from grocery purchases, and Broda and Weinstein (2010) use barcode data to study turnover in product variety. The study most closely related to the present work is Couture (2014), which estimates consumer gains from access to variety of restaurants.

This study contributes to the literature by quantifying consumer preferences for variety in nightlife and modelling how these preferences impact nightlife industry dynamics and the level of nightlife services provided. I construct and estimate a dynamic structural model

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\(^1\)As Zimmerman (2008) notes, policy makers often provide a rationale for encouraging nightlife in terms of the “creative class” concept advanced in Florida (2002) and Florida (2005), which asserts that a city will benefit from the influx of highly educated professionals if those professionals find the city a pleasant and enjoyable place to live.
of nightlife venue entry and exit using license data from Chicago. The model accounts for
the “vibrancy” of nightlife districts. That is, in situations where consumers attain higher
utility by choosing to go out, more consumers choose to go out and profit can potentially be
higher — not only for a new entrant, but also for incumbent venues. As the model predicts
entry and exit rates as a function of structural parameters, I can estimate the structural
parameters using only data on entry and exit; this strategy is necessary in the present
context, where more-detailed information is generally unavailable.

Structural estimation allows for the measurement of consumer preferences for variety as
well as the evaluation of counterfactual scenarios which take into account the dynamic re-
sponses of venues to each others’ entry and exit decisions. I develop a structural model which
closely matches the conditions in the Chicago nightlife market. In particular, the model of
individual venues as decision-making agents corresponds to the reality that nightlife venues
in Chicago are generally atomistic firms rather than centrally-owned chains with coordi-
nated decisions. Moreover, the model includes endogenous price variation across venues in
response to consumers’ demand. The estimation strategy allows for direct control of local
demographic and regulatory conditions, which assists in distinguishing venue aggregation
from zoning restrictions and other local conditions; as Datta and Sudhir (2013) note, ac-
counting for local regulation is essential for accurate measurements of the benefits of firm
colocation.

This study also contributes to the broader urban economics literature which attempts
to explain the observed colocation of economic activity and similar firms in particular. As
discussed by Rosenthal and Strange (2004), Puga (2010), and many others, positive agglom-
eration effects for firms play a significant role in explaining the structure and concentration
of economic activity in cities. More specifically, several theoretical studies including discuss
aspects of consumers’ preferences and decision process which could rationalize colocation
in industries which offer widely differentiated products. Wolinsky (1983) studies the role of
consumers’ imperfect information, while Fischer and Harrington (1996) and Konishi (2005)
raise the related possibility of taste uncertainty. In these studies, the consumers’ behaviour
can lead to higher profit for colocating firms than for spatially distant firms.

The structural model I develop and estimate in this study attempts to explain observed
patterns of venue location through the benefit consumers receive from access to many nearby venues. This complements previous reduced-form studies of observed firm colocation including Picone, Ridley and Zandbergen (2009), Freedman and Kosová (2012), and Krider and Putler (2013) and structural studies including Davis (2006), Jia (2008), and Dunne et al. (2013).

Data availability on the operations of nightlife venues is generally limited. Accordingly, this study builds upon a literature in industrial organization which uses entry and exit information to estimate the profit function, including Bresnahan and Reiss (1991), Pesendorfer and Schmidt-Dengler (2003), Aguirregabiria and Mira (2007), Ryan (2012), Collard-Wexler (2013), Dunne et al. (2013), and Nishida (2015). This appears to be one of the first studies to adopt the continuous-time dynamic discrete choice framework proposed by Arcidiacono et al. (2012). This framework allows for the computationally-tractable estimation of a full-featured structural model with a large state space. In particular, it allows for the consideration of spillovers both within and between types of nightlife venues.

The results of the estimation suggest that consumers have very strong preferences for access to variety in nightlife venues. Consumers gain substantial utility from access to nearby venues of different types. In particular, their preference for access to variety is highest among venues without music, dancing, or other amenities (i.e. bars) and somewhat lower for nightclubs, performance venues, and other venue types. Overall, these preferences for variety are somewhat stronger than the consumer preferences for variety in restaurants discussed in Couture (2014) and comparable to the most variety-specific goods in Broda and Weinstein (2006) and Broda and Weinstein (2010). These results are robust to substantial changes in specification. In the median neighbourhood, one new venue without

\footnote{Sales data is available in some cases. Abbring and Campbell (2005) use monthly liquor sales history from a sample of Texas bars to study the survival of new firms. However, this sales data is not linked with other attributes of the venue such as the type of services it provides and therefore it is less helpful for the present study. Note that self-reported consumer expenditure on nightlife is prone to under-reporting and therefore unreliable; Bee, Meyer and Sullivan (2012) describe alcohol spending in the Consumer Expenditure Survey’s diary survey as “especially badly reported” compared to other expenditure categories.}

\footnote{In addition to the methodology, several other studies including Pesendorfer and Schmidt-Dengler (2003), Bajari, Benkard and Levin (2007), and Aguirregabiria and Mira (2007) and Pakes, Ostrovsky and Berry (2007) have described estimation strategies for inferring the structural profit function from a small set of observed actions. I adapt the framework suggested in Arcidiacono et al. (2012) because the continuous-time framework allows for full use of available data in a rich state space while preserving computational tractability.}
music, dancing, or other amenities raises consumer welfare for nightlife consumers to a level equivalent to a 13.5% increase in nightlife expenditure.

Moreover, I find that consumer preference for variety is strong enough that in many observations a (counterfactual) new entrant would increase the profit for incumbent competitors. That is, the estimated parameter values predict sufficiently strong preference for variety that the additional demand from a new venue largely compensates the effect of additional competition on profits in many cases. This effect holds for incumbents of the same type as the entrant as well as for incumbents of different types.

However, consumers’ welfare in terms of access to nightlife variety is limited by the high barriers to entry faced by nightlife entrepreneurs. These high barriers can partially be attributed to very local license restrictions (which vary widely across the city) although other barriers (including city-wide regulatory cost as well as non-regulatory costs) are much more significant. The estimated barriers to entry correspond closely with estimates in the industry literature.

The remainder of the paper is organized as follows. First, I outline a structural model for venue profits and venues’ entry and exit decisions in a framework that lends itself to maximum likelihood estimation and counterfactual evaluation. Then, I estimate this model using business license data from Chicago. Finally, I discuss the results of this estimation in the context of consumer preferences for variety and conduct counterfactual exercises to investigate the role of these preferences in determining nightlife industry dynamics.

2.2 Model

To parametrize consumer preferences over nightlife amenities and the relationship between consumer preferences and venue entry and exit decisions, I describe a structural model for the nightlife industry. I build this model in stages. First, I outline a static model for venue profit and derive theoretical results that show venue profits may increase with the number of nearby venues due to consumer preferences for more variety in nightlife. Then, I embed this model of venue profit in a dynamic model that describes nightlife venue entry and exit by forward-looking discounted-profit maximizing venues. This dynamic model lends itself
to the estimation strategy described by Arcidiacono et al. (2012).

Before proceeding, it will be helpful to explicitly discuss the modelling choices for consumers’ preferences and venues’ decision-making processes. I provide details on parametrization and estimation in further detail below.

I model consumer preferences using a constant substitution of elasticity (CES) utility function. This provides a tractable parameterization of consumer preferences in terms of variety. As well, the CES functional form makes the results broadly comparable with other estimates of consumer gains from access to variety, including Broda and Weinstein (2006), Broda and Weinstein (2010), and Couture (2014). However, as the model in this paper allows for the possibility that consumers do not go out and consume nightlife, it is not entirely identical to these other models. This adjustment seems reasonable in the context of nightlife, where consumers frequently choose not to consume based on the quality of the outside options. In comparison, it seems highly unlikely that consumers would choose not to consume, e.g., groceries regardless of any outside options.

As is common in the literature, this model abstracts from the individual-level microfoundations of this preference for variety. However, several explanations are possible and mutually compatible. If venues have idiosyncratically high-quality and low-quality nights, then risk-averse customers may gain higher utility from going out in a neighbourhood with many venues as this would minimize their search costs in finding a high-quality venue. This is compatible with both the imperfect-information model developed by Wolinsky (1983) and the taste-uncertainty model investigated by Fischer and Harrington (1996) and developed by Konishi (2005). Nightlife patrons seeking to meet new people may prefer situations with many nearby venues to maximize their prospects. All of these scenarios would lead to the empirically-observed preference for neighbourhoods with many venues\(^4\).

I model venues’ entry and exit decisions in a continuous-time environment. In this environment, potential entrants decide whether to enter the market and incumbent venues decide whether to exit. Agents are not able to update these decisions continuously. Instead, they receive opportunities at stochastic intervals via a Poisson process which delivers opport-

\(^{4}\text{As shown by Anderson, De Palma and Thisse (1992) and noted in Couture (2014), the CES utility model yields equivalent choices to a model with logit shocks to consumer-choice pairs.}\)
tunities at a constant rate. At each opportunity, a potential entrant may decide whether to enter and a potential incumbent may decide whether to exit. Transitions to the policy and demographic environment are governed by a Poisson process as well. While it requires some additional notation, the continuous-time approach offers several advantages over standard discrete-time approaches:

- Allowing for continuous time (as opposed to aggregating daily liquor license observations to a larger time scale) allows for use of all available information in the data set.

- In continuous time, simultaneous moves by two agents arise with zero probability. Accordingly, agents decisions’ need not be integrated over all possible moves by other agents (and all possible exogenous transitions to the environment). This drastically reduces the computational burden required for maximum likelihood estimation and allows for tractable estimation of a richer model.

- Discrete time periods imply that all agents all have their sole opportunity to make decisions at the same time, once per period. For example, discrete monthly periods would imply that venues decide whether to exit and enter the market simultaneously at the beginning of every month. Stochastic decision times likely represent a closer approximation to reality and relax the assumption that all decisions occur simultaneously.

2.2.1 Static model

The environment for the static model of the nightlife industry consists of venues and consumers. Specifically, the environment includes \( n_\ell \) venues of each type \( \ell \in 1, 2, \ldots, L \). Each type of venue provides a different kind of nightlife service to consumers. For example, bars are one type while nightclubs are another. These venues serve a market represented by a continuum of consumers of measure \( \bar{N} \). Each consumer has a budget \( w \) for nightlife services. Venues of a given type are symmetric — i.e., they face the same profit maximization problem. Consumers’ utility includes preference for variety within and across venue types.
The consumer decides whether to go out and consume nightlife services based on the realization of a reservation utility shock. Venues set their prices to maximize profit optimally in response to each others’ prices and consumer preferences.

**Consumer preferences**

Consumer preferences in the model consist of a nested CES utility for consumption across nightlife venues with a reservation shock. The inner nest accounts for preferences between venues of the same type while the outer nest accounts for preference for variety across different types of venue. The reservation shock represents the possibility that consumers choose not to go out and consume any nightlife services. Because of the reservation shock, the number of patrons for nightlife services varies with the number and types of venues.

As mentioned previously, I use a constant elasticity of substitution (CES) framework to describe consumer preferences. Specifically, I assume that consumer utility has the following functional form:

\[
U(q) = \max \left\{ \left( \sum_{\ell} \left( \sum_i q_{i\ell}^{\rho-1} \right)^{\frac{\rho\eta-1}{\rho-1}} \right)^{\frac{\eta}{\eta-1}}, V^* \right\}
\] (2.1)

The first case on the right-hand side of Equation 2.1 represents a situation where the consumer chooses to go out and consume nightlife services, while the second case represents a situation where the consumer chooses the reservation utility of not going out. The parameter \(\rho\) is the constant elasticity of substitution between venues of type \(\ell\) while the parameter \(\eta\) is the constant elasticity of substitution across venues of different types. By assumption, \(\rho_\ell > \eta > 2\) for all types \(\ell\) — that is, consumers are more willing to substitute between venues of the same type than across different types.

In the case where the consumer chooses to go out, the consumer chooses the level of

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5 This study focuses on consumers' preference for access to a variety of venues. That is, the utility function described in this model addresses the preferences of nightlife consumers. As discussed in further detail below, nightlife externalities such as noise and crime may also enter residents' utility functions. These additional preferences regarding negative externalities are beyond the scope of this model of the nightlife industry. However, they are relevant to policymakers considering the general equilibrium effects of nightlife industry policy.

6 The assumption \(\eta > 2\) is particular to the present model with the added reservation shock. It is required to ensure a consistent and unique solution as shown in Proposition 1. In the more general model without the reservation utility shock, \(\eta > 1\) is sufficient.
consumption $q^D_{ii}$ for venue $i$ of type $\ell$ subject to the budget constraint $\sum_i \sum_\ell p_{ii} q_{ii} \leq w$. For notational convenience, introduce the usual CES price indices $P_\ell = \left( \sum_i p_{ii}^{1-\rho_\ell} \right)^{\frac{1}{1-\rho_\ell}}$ and $P = \left( \sum_\ell P_\ell^{1-\eta} \right)^{\frac{1}{1-\eta}}$. Then, solving the consumer’s problem for a given vector of prices $p = \{p_{11}, p_{11}, \ldots, p_{1n_1}, \ldots, p_{\ell i}, \ldots, p_{L1}, p_{L2}, \ldots, p_{Ln_L}\}$ gives the following demand for nightlife services from venue $i$ of type $\ell$:

$$q^D_{ii} = p_{ii}^{-1} \left( \frac{p_{ii}}{P_\ell} \right)^{-\rho} \left( \frac{P_\ell}{P} \right)^{-\eta} w$$  \hspace{1cm} (2.2)

Substituting this demand into Equation 2.1 yields the following expression for the indirect utility $V(p)$:

$$V(p) = w P^{\eta-1} \sum_\ell P_\ell^{-\eta}$$  \hspace{1cm} (2.3)

The reservation shock $V^*$ in Equation 2.1 is a uniformly distributed random variable on $[0, 1]$. (Setting the maximum value of the shock to unity normalizes the prices in the model.) Each of the $\tilde{N}$ measure-zero consumers experiences a separate realization of the shock. Therefore, the total measure of consumers opting to go out and consume nightlife services is $N = \tilde{N} \min \{V(p), 1\}$. That is, $N$ increases with the value of going out up to the point where all consumers choose to go out, at which point $N = \tilde{N}$. This feature represents the “vibrancy” aspect of qualitative discussions of nightlife amenities. In equilibrium, a neighbourhood with a wider variety of venues (and therefore higher utility to going out) will induce more consumers to choose to go out and consume nightlife.

It is worth noting that this model does not allow consumers to choose between neighbourhoods. Instead, they choose only whether to go out. Allowing consumers to choose to go out from a range of neighbourhoods would likely lead to larger estimated spillover effects as consumers choose to go out in higher-utility neighbourhoods; therefore, the estimates in this paper potentially underestimate the true spillover magnitude. However, these changes would likely be relatively small, as any change in venues’ strategies would reflect their ability to unilaterally change the utility of the neighbourhood relative to other neighbourhoods, which is likely limited. In more practical terms, a model that allowed consumers to choose one of several dozen neighbourhoods would quickly become computationally intractable.
**Profit maximization**

Each venue sets the price of its services to maximize profit. Venues face the demand \( q_{D_i} \) (as given by Equation 2.2) from measure \( N = \bar{N} \min \{V(p), 1\} \) consumers. A venue of type \( \ell \) faces a constant marginal cost of production \( c_\ell \) as well as a fixed cost of production \( \kappa_\ell \).

This gives the following profit maximization problem:

\[
\pi_{\ell i} = \max_{p_{\ell i}} \left\{ (p_{\ell i} - c_\ell) \left( \frac{p_{\ell i}}{P_{\ell}} \right)^{-\rho} \left( \frac{P_{\ell}}{P} \right)^{-\eta} P^{-1} \bar{N} \min \{V(p), 1\} w - \kappa_\ell \right\} \tag{2.4}
\]

Each venue sets its price as a best response to the other venues’ prices. Therefore, the equilibrium concept is a Bertrand-Nash equilibrium. Taking the first-order condition and rewriting in terms of \( s_{\ell i} = \frac{q_{\ell i}}{\sum_{i'} q_{\ell i'}} = p_{\ell i}^{1-\rho_{\ell}} P^{\rho_{\ell}-1} \) (the share of demand for venues of type \( \ell \) going to venue \( i \)) and \( S_\ell = \frac{\sum_{i'} q_{\ell i'}}{\sum_i q_{\ell i'}} = P^{1-\eta} P^{\eta}-1 \) (the share of total demand going to all venues of type \( \ell \)) yields the following optimization condition:

\[
p_{\ell i} = \begin{cases} 
(1 + \frac{1}{\rho_{\ell} - \rho_{\ell} - (\rho_{\ell} - 1) S_{\ell} s_{\ell i} - (\eta - 1) S_{\ell} s_{\ell i} - 1}) c_\ell & \text{if } V(p) < 1 \\
(1 + \frac{1}{\rho_{\ell} - (\rho_{\ell} - \eta) S_{\ell} s_{\ell i} - (\eta - 1) S_{\ell} s_{\ell i} - 1}) c_\ell & \text{if } V(p) \geq 1 
\end{cases} \tag{2.5}
\]

By assumption, venues in a given sector \( \ell \) are symmetric. Therefore, they must set the same prices in equilibrium, which means the share of total demand to venue \( i \) of type \( \ell \) is \( s_{\ell i} = \frac{1}{n_\ell} \). This yields the following optimal pricing strategy.

\[
p_{\ell i} = \begin{cases} 
(1 + \frac{1}{n_\ell (\rho_{\ell} - 1) - (\rho_{\ell} - \eta) S_{\ell} s_{\ell i} - (\eta - 1) S_{\ell} s_{\ell i} - 1}) c_\ell & \text{if } V(p) < 1 \\
(1 + \frac{n_\ell}{n_\ell (\rho_{\ell} - 1) - (\rho_{\ell} - \eta) S_{\ell} s_{\ell i} - (\eta - 1) S_{\ell} s_{\ell i} - 1}) c_\ell & \text{if } V(p) \geq 1 
\end{cases} \tag{2.6}
\]

Considering Equation 2.6 over all sectors \( \ell \) gives a system of \( L \) equations for the prices over all sectors \( \ell \in 1, 2, \ldots, L \). This is not a closed-form solution, as the industry shares \( S_1, S_2, \ldots, S_L \) appear on the denominator on the right-hand side and these are a function of the prices. In general, no closed form solution exists for the equilibrium prices. However,
the following theorem justifies the use of numerical methods to solve Equation 2.6 for equilibrium prices.

**Proposition 1.** *There exists a unique equilibrium set of prices $p^*$ which solves Equation 2.6.*

*Proof. See Appendix A.*

Figure 2.1 shows the equilibrium profits for a single venue in a two-sector example as a function of the number of venues in each sector. In these examples, profit is non-monotonic in the number of competitor venues. In general, the model allows for venue profit to increase in the number of venues.

This result also has an intuitive explanation. A greater variety of nightlife options means more consumers’ utilities exceed their reservation shocks and therefore more consumers choose to consume at the venues. If an additional venue causes enough consumers to opt to go out and consume nightlife that this positive effect on revenue dominates the negative effect of additional competition, then profit for an incumbent venue will rise when a new venue enters the market. That is, the consumer preference for variety represents a positive demand-side agglomeration effect from the venues’ point of view. The strength of this effect depends on the CES parameters $\rho_l$ and $\eta$ — lower elasticity of substitution corresponds to stronger preferences for variety and therefore higher profits for venues which are located near other venues. (Conversely, in the case where the elasticity of substitution is $\infty$, the
venues are indistinguishable from the consumers’ point of view and the venue’s problem reduces to the standard Bertrand oligopoly.

However, note that profit will not increase indefinitely with the number of venues. Regardless of parameter values the consumer utility of going out will always reach $V(p) = 1$ for sufficiently many venues:

**Proposition 2.** There exists some $\bar{n} \in \mathbb{N}$ such that, when $n_\ell \geq \bar{n}$ for $\ell \in 1, 2, \ldots, L$, the equilibrium prices give $V(p) \geq 1$.

**Proof.** See Appendix B.

Once $V(p) = 1$, with higher $n_\ell$ the equilibrium prices eventually converge to the standard CES pricing strategy $p_{\ell i} = \frac{\rho}{\rho \ell - 1} c_\ell$ and (as in the standard CES case) profit declines with additional venues. Accordingly, while the agglomerative benefits in this model may provide higher profits to venues located near other venues, the benefit does not grow until venue density and profits become infinite. Once the neighbourhood is maximally vibrant and everyone who would go out is already going out, the profit can no longer increase with the number of venues in the neighbourhood.

Figure 2.2 shows the corresponding consumer welfare as a function of the number of venues in each sector. Note that this includes not only the consumers who choose to go out, but also the consumers whose reservation utility exceeds the utility of going out. As shown, consumer utility is highest in situations with many venues.

### 2.2.2 Dynamic model

The static model presented above describes venue profits as a function of neighbourhood attributes and the number of competitors. I connect this profit function to venue entry and exit data with a dynamic model of entry and exit decisions. In this model, agents observe each others’ actions and the state of the environment and make entry and exit decisions as a best response to their beliefs about each others’ actions. In equilibrium, these beliefs about each others’ actions are consistent and based upon current observable state variables; therefore, the solution concept is a Markov-Nash equilibrium.
The agents in the dynamic model are the operators of individual venues — specifically, entrepreneurs who could start a new venue and incumbents with existing venues. As discussed previously, agents receive opportunities to move in continuous time according to the realization of a Poisson process. Upon receiving an opportunity, potential market entrants make the decision whether to enter or stay out of the market and incumbent venues make the decision whether to continue or leave the market. Once an incumbent leaves the market, they have left the market forever. A potential entrant must pay a sunk cost to enter while an exiting incumbent receives an exit payoff.

The sunk cost of entry and the exit payoff consist of a deterministic component and a stochastic component. I discuss this in further detail below. The deterministic component of each agent’s shock is mutual common knowledge, while the stochastic component is private knowledge for the agent and realized only once the agent receives a move opportunity. These shocks capture the economic reality that entrepreneurs may face barriers to entry.
and owners may receive gains from the sale of capital goods upon exiting the market. As well, they give rise to a nondegenerate probability distribution for entry and exit upon receiving a move opportunity. This allows for the use of observed entry and exit rates to identify profit functions, which is a key aspect of the estimation procedure outlined below.

Agents are assigned to discrete neighbourhoods indexed by \( m \). That is, each entrant has a specific neighbourhood in which it may choose to enter and each incumbent may either continue to operate in its neighbourhood or exit the market. Each neighbourhood has \( n_m = (n_{m1}, n_{m2}, \ldots, n_{mL}) \) incumbent venues of each type \( \ell \in 1, 2, \ldots, L \) as well as \( \nu_\ell \) entrants of type \( \ell \). (As the number of potential entrants is unobservable, I treat this as a parameter to be estimated.) As well, each neighbourhood has some persistent demographic attributes \( d_m \) which affect the profit and some persistent regulatory stringency \( r_m \) which affects the size of the sunk cost of entry\(^7\). Potential entrants receive opportunities to enter the market according to a Poisson process with rate parameter \( \alpha \) while incumbent venues receive opportunities to exit the market according to a Poisson process with rate parameter \( \lambda \). I assume that agents discount the future at constant rate \( \delta \).

It is worth discussing the assumption that potential entrants have a single neighbourhood in which they can choose to enter. One may interpret an opportunity for an entrepreneur to enter as a particular piece of commercial real estate becoming available as a potential future venue. Insofar as a commercial real estate vacancy of a suitable size and configuration is a necessary precursor to opening a new nightlife venue (and building a nightlife venue on a nightlife venue on an empty lot is likely infeasible in the context of Chicago) this is likely a plausible interpretation. A richer model could allow potential entrants to choose a neighbourhood for entry. However, the much larger state space relevant to each agent’s decisions (i.e., the state of each market) would yield a computationally intractable model. This restriction may also be justified if we assume that entrants have some particular knowledge of local conditions within the neighbourhood.

Each agent forms its value function based on its consistent belief of other agents’ entries and exits as well as its expectations of its own move opportunities. An incumbent venue receives the flow profit \( \pi_\ell \) as specified by Equation 2.4. Let \( t_\ell \) be a vector with 1 as element

\(^7\)Suzuki (2013) shows that local land use regulations may represent a significant barrier to entry for new firms.
ℓ and 0 as all other elements — i.e., \( n + \nu \ell \) is the vector of incumbent venues after a new venue of type \( \ell \) enters. The value function for an incumbent venue of type \( \ell \) (as a function of the number of venues \( n_m \), the demographic attributes \( d_m \), and the regulatory conditions \( r_m \)) is as follows:

\[
V_c^\ell(n_m, d_m, r_m) = \left[ \delta + \sum_{\ell'} \left( \nu_{\ell'} \alpha_{\ell'} + n_{\ell'} \lambda_{\ell'} \right) \right]^{-1} \times \left[ \pi(n_m, d_m) + \sum_{\ell'} \left( (n_{\ell'} - I(\ell, \ell')) \lambda_{\ell'} \sigma_{\ell'}^c(n_m, d_m, r_m) V_c^\ell(n_m + \nu_{\ell'}, d_m, r_m) + \nu_{\ell'} \alpha_{\ell'} \sigma_{\ell'}^c(n_m, d_m, r_m) V_c^\ell(n_m - \nu_{\ell'}, d_m, r_m) \right) + \lambda_e E \left[ \max \{ V_c^\ell(n_m, d_m, r_m), \psi_e^l + \xi_e \} \right] \right] \tag{2.7}
\]

In Equation 2.7, the second line accounts for entries and exits by other agents while the third line accounts for the incumbent’s decision to remain or exit conditional on receiving a move opportunity. Recall that in the continuous-time environment it is unnecessary to account for the possibility of multiple simultaneous transitions as this is a measure-zero event.

The value function for a potential entrant of type \( \ell \) which has not yet chosen to enter the market is similar, although the potential entrant receives no flow of profit:

\[
V_e^\ell(n_m, d_m, r_m) = \left[ \delta + \sum_{\ell'} \left( \nu_{\ell'} \alpha_{\ell'} + n_{\ell'} \lambda_{\ell'} \right) \right]^{-1} \times \left[ 0 + \sum_{\ell'} \left( n_{\ell'} \lambda_{\ell'} \sigma_{\ell'}^e(n_m, d_m, r_m) V_e^\ell(n_m + \nu_{\ell'}, d_m, r_m) + \nu_{\ell'} \alpha_{\ell'} \sigma_{\ell'}^e(n_m, d_m, r_m) V_e^\ell(n_m - \nu_{\ell'}, d_m, r_m) \right) + \alpha_e E \left[ \max \{ V_e^\ell(n_m, d_m, r_m), V_c^{\ell}(n_m + \nu_{\ell}, d_m, r_m) - \psi_x(r_m) + \xi_e \} \right] \right] \tag{2.8}
\]

These value functions lead directly to the conditional choice probabilities for venue entry and exit decisions. Conditional on receiving an entry opportunity, a potential entrant will choose to enter (and become an incumbent venue) only if the value of being an incumbent exceeds the value of remaining an entrant less the entry sunk cost. Similarly, conditional on receiving an exit opportunity, an incumbent will exit only if the exit payoff exceeds the value of continuing as an entrant. The entry cost \( \psi_e(r) + \xi_e \) and the exit payoff \( \psi_x + \xi_x \) consist of deterministic components \( \psi_e(r) \)\(^8\) and \( \psi_x \) plus independent and identically distributed stochastic components \( \xi_e \) and \( \xi_x \). As noted previously, the fixed components of these shocks

\(^8\)To reflect the possibility that local land-use regulation impacts the sunk cost of entry, I allow \( \psi_e \) to vary with regulatory stringency \( r \).
are mutual common knowledge, while the realizations of the stochastic components are private information for each agent upon receiving a move opportunity. For tractability, I assume Type-I extreme value forms for the stochastic components.

Therefore, conditional on receiving move opportunities, the conditional choice probabilities of entry \( \sigma_e^{\ell} \) and exit \( \sigma_x^{\ell} \) are as follows:

\[
\sigma_e^{\ell}(n, d, r) = 1 - \exp\left(-\exp(-V_e^{\ell}(n, d, r) - V_c^{\ell}(n, d, r) + \psi_e(r))\right)
\] (2.9a)

\[
\sigma_x^{\ell}(n, d, r) = 1 - \exp\left(-\exp(-V_e^{\ell}(n, d, r) - \psi_x)\right)
\] (2.9b)

Recall that \( \alpha^{\ell} \) and \( \lambda^{\ell} \) denote the arrival rate for entry and exit opportunities for entrants and incumbents of type \( \ell \). Therefore, the entry rate for potential entrants \( h_e^{\ell}(n, d, r) \) and the exit rate for current incumbents \( h_x^{\ell}(n, d, r) \) are as follows:

\[
h_e^{\ell}(n, d, r) = \alpha^{\ell}\sigma_e^{\ell}(n, d, r)
\] (2.10a)

\[
h_x^{\ell}(n, d, r) = \lambda^{\ell}\sigma_x^{\ell}(n, d, r)
\] (2.10b)

Equation 2.10 states that the observed entry and exit rates are equal to the rates at which agents receive move opportunities multiplied by the conditional choice probabilities of taking those opportunities. Venue entry and exit rates are observable in the data. In the estimation strategy below, I outline a scheme for connecting the observed entry and exit rates to the flow profit. Differences in venue entry and exit rates between states correspond to differences in the flow profit and the barriers to entry. I use these differences to identify the structural parameters of the model.

### 2.2.3 Estimation strategy

I estimate this model using a maximum likelihood strategy following Arcidiacono et al. (2012). The observable outcome of interest in this strategy is the state transition — that is, the entry or exit of a venue. The estimation procedure identifies the values for the structural parameters which maximize the joint likelihood of the wait time between transitions and
the type of transition.

The estimation procedure comprises several stages, as follows:

1. Obtain nonparametric estimates $\hat{h}_e^\ell$ and $\hat{h}_x^\ell$ for the observed venue entry and exit rates.

2. Use the estimates $\hat{h}_e^\ell$ and $\hat{h}_x^\ell$ to write the conditional choice probabilities of entry and exit $\hat{\sigma}_e^\ell(n_{mt},d_m,r_m|\theta)$ and $\hat{\sigma}_x^\ell(n_{mt},d_m,r_m|\theta)$ in terms of the structural parameters.

3. Find the value of the structural parameters $\hat{\theta}$ which maximizes the likelihood function of the observed transitions.

Because the conditional choice probabilities $\hat{\sigma}_e^\ell(n_{mt},d_m,r_m|\theta)$ and $\hat{\sigma}_x^\ell(n_{mt},d_m,r_m|\theta)$ represent best responses to the estimated entry and exit rates $\hat{h}_e^\ell$ and $\hat{h}_x^\ell$ by construction, the second step enforces that the estimated result represents a Markov-Nash equilibrium.

I estimate a single parameter $\eta$ for the constant elasticity of substitution between sectors and a single parameter $w$ for the consumer’s nightlife budget. For each venue type $\ell$, I estimate a separate value for the within-sector constant elasticity of substitution $\rho_\ell$, the marginal cost of production $c_\ell$, the move arrival rates $\alpha_\ell$ and $\lambda_\ell$, the number of potential entrants $\nu_\ell$ and the exit payoff $\psi_x^\ell$. I estimate the market size $\bar{N}$ the fixed cost of operation $\kappa_\ell$ as a function of local demographic and built environment conditions and the sunk cost of entry $\psi_e^\ell$ as a function of local regulatory conditions.

At this point, it will be helpful to introduce some additional notation. For a given neighbourhood $m$, let $t = 1, 2, \ldots, T_m$ index the observed transitions (i.e., entries or exits). Let $\tau_{mt}$ be the wait time before transition $t$, let $n_{mt} = (n_{mt1}, n_{mt2}, \ldots, n_{mtL})$ denote the vector of venues of each type $\ell$ before transition $t$, and let $e_{mt\ell}$ and $x_{mt\ell}$ be indicator variables for whether the transition $t$ in neighbourhood $m$ was an entry of type $\ell$ or an exit of type $\ell$. As a slight abuse of notation, let $T_m + 1$ denote the period from the last observed transition to the end of the sample\(^9\). Then, the log-likelihood of the observed transitions \{\tau_{mt}, n_{mt}, e_{mt\ell}, x_{mt\ell}\} can be written as a function of these entry and exit rates $h_e^\ell$ and $h_x^\ell$.

\(^9\)In this last period, the state after the next transition is clearly unobservable. However, the duration of the wait before a transition is itself informative, and therefore included in the likelihood function.
as follows:

\[
LLH \left( \{\tau_{mt}, n_{mt}, \epsilon_{mt}\ell, x_{mt}\ell} \mid h^e_{\ell}, h^x_{\ell} \right) = \\
\sum_m \left[ \sum_{T+1}^{T_m+1} \left( \sum_{t=1}^{T_m=t \tau_{mt}} \left( n_{mt}\ell h^e_{\ell}(n_{mt}, d_m, r_m) + \nu_{t} h^x_{\ell}(n_{mt}, d_m, r_m) \right) + \right) \\
\sum_{t=1}^{T_m} \sum_{\ell} \left( x_{mt}\ell n_{mt}\ell \log h^e_{\ell}(n_{mt}, d_m, r_m) + \epsilon_{mt}\ell \nu_{t} \log h^x_{\ell}(n_{mt}, d_m, r_m) \right) \right]
\]

Equation 2.11 gives the joint likelihood of the observed wait time between transitions and the observed type of each transition. Specifically, the first sum expresses the likelihood of the observed wait time between transitions and the second sum expresses the likelihood of the observed type of each transition (conditional on observing a transition). Below, I maximize this joint likelihood to obtain the structural parameters. Taking first-order conditions yields closed-form expressions for the nonparametric entry and exit rates:

\[
h^e_{\ell}(n, d, r) = \left[ \sum_m \sum_{t=1}^{T_m+1} \mathbbm{1}_{mt} \{ (n, d, r) = (n_{mt}, d_{mt}, r_{mt}) \} \tau_{mt} \right]^{-1} \left[ \sum_m \sum_{t=1}^{T_m} \mathbbm{1}_{mt} \{ (n, d, r) = (n_{mt}, d_{mt}, r_{mt}) \} \epsilon_{mt}\ell \right]
\]

(2.12a)

\[
h^x_{\ell}(n, d, r) = \left[ \sum_m \sum_{t=1}^{T_m+1} \mathbbm{1}_{mt} \{ (n, d, r) = (n_{mt}, d_{mt}, r_{mt}) \} \tau_{mt} \right]^{-1} \left[ \sum_m \sum_{t=1}^{T_m} \mathbbm{1}_{mt} \{ (n, d, r) = (n_{mt}, d_{mt}, r_{mt}) \} x_{mt}\ell \right]
\]

(2.12b)

In Equation 2.12, \( \mathbbm{1} \) denotes the indicator function. The entry and exit rates in Equation 2.12 can be estimated directly from the data. Denote the results of this estimation by \( \hat{h}^e_{\ell} \) and \( \hat{h}^x_{\ell} \).

Next, I use these first-stage estimates \( \hat{h}^e_{\ell} \) and \( \hat{h}^x_{\ell} \) to write the value functions in terms of structural parameters\(^\text{10}\). Arcidiacono et al. (2012) shows that the agents’ value functions can be written in terms of \( h^e_{\ell} \) and \( h^x_{\ell} \), the move arrival rate parameters \( \alpha \) and \( \lambda \), and the entry sunk cost and exit payoff \( \psi^e_{\ell} \) and \( \psi^x_{\ell} \):

\[
V^e_{\ell}(n, d, r \mid h^e_{\ell}, h^x_{\ell}, \alpha, \lambda, \psi^e_{\ell}, \psi^x_{\ell}) = \\
\psi^e_{\ell} - \psi_e(r) + \log \frac{1 - \lambda^{-1} h^x_{\ell}(n, d, r)}{\lambda^{-1} h^x_{\ell}(n, d, r)} + \log \frac{1 - \alpha^{-1} h^e_{\ell}(n, d, r)}{\alpha^{-1} h^e_{\ell}(n, d, r)}
\]

(2.13a)

\(^\text{10}\)It would be possible to address this stage using numerical value function iteration on Equations 2.7 and 2.8. However, the strategy outlined here is much faster and yields exact results.
Recall that $\alpha^{-1}_\ell h^e_\ell$ is the probability of entry conditional on receiving a move opportunity while $\lambda^{-1}_\ell h^x_\ell$ is the probability of exit conditional on receiving a move opportunity. The value of an agent’s decision conditional on receiving a move opportunity can be written in terms of the same objects\textsuperscript{11}:

$$
\mathbb{E} \left[ \max \{ V^e_\ell(n,d,r), V^c_\ell(n_\ell + \iota_\ell, d, r) - \psi_e(r) + \varepsilon_e \} \mid h^e_\ell, h^x_\ell, \alpha, \lambda, \psi^e_\ell, \psi^x_\ell \right] =
- \log(1 - \alpha^{-1}_\ell h^e_\ell(n, d, r)) + \gamma \quad (2.14a)
$$

$$
\mathbb{E} \left[ \max \{ V^c_\ell(n, d, r), \psi^x_\ell + \varepsilon_x \} \mid h^c_\ell, h^x_\ell, \alpha, \lambda, \psi^e_\ell, \psi^x_\ell \right] =
- \log(1 - \lambda^{-1}_\ell h^x_\ell(n, d, r)) + \gamma \quad (2.14b)
$$

Substituting the first-stage estimation results $\hat{h}^e_\ell$ and $\hat{h}^x_\ell$ into Equations 2.13 and 2.14 gives consistent estimates for the value functions. Substituting these estimates into the right-hand sides of Equation 2.7 and 2.8 yields expressions for the value functions in terms of the structural parameters (including the structural parameters of the profit function). Substituting these structural expressions for the profit function into Equation 2.9 gives the choice probabilities for venue entry and exit (conditional on receiving a move opportunity) as a function of the structural parameters. Denote these structural conditional choice probability estimates as $\hat{\sigma}^e_\ell(n_{mt}, d_m, r_m | \theta)$ and $\hat{\sigma}^x_\ell(n_{mt}, d_m, r_m | \theta)$ where $\theta$ is the vector of parameters including the move opportunity rates $\alpha$ and $\lambda$, the number of potential entrants $\nu$, and all parameters of the profit function. This yields the following expression for the log-likelihood of the observed transitions in terms of the structural parameters:

$$
LLH\left( \left\{ \tau_{mt}, n_{mt}, e_{mt\ell}, x_{mt\ell} \right\} \mid \theta \right) =
\sum_m \left[ \sum_{t=1}^{T_{m+1}} (-\tau_{mt}) \sum_\ell \left( n_{mt\ell} \lambda_\ell \hat{\sigma}^e_\ell(n_{mt}, d_m, r_m | \theta) + \nu_\ell \alpha_\ell \hat{\sigma}^e_\ell(n_{mt}, d_m, r_m | \theta) \right) +
\sum_{t=1}^{T_m} \sum_\ell \left( x_{mt\ell n_{mt\ell}} \log \lambda_\ell \hat{\sigma}^x_\ell(n_{mt}, d_m, r_m | \theta) + e_{mt\ell \nu_\ell} \log \alpha_\ell \hat{\sigma}^e_\ell(n_{mt}, d_m, r_m | \theta) \right) \right] \quad (2.15)
$$

\textsuperscript{11}In Equation 2.14 $\gamma \approx 0.5772156649$ is the Euler constant. This constant arises from the integration over the stochastic components of the entry cost and exit payoff. It is specific to the assumed Type-I extreme value functional form of these shocks.
I solve numerically for the parameter vector $\hat{\theta}$ which maximizes the structural log-likelihood as specified by Equation 2.15. This estimate $\hat{\theta}$ forms the basis of the empirical results of this study.

It remains to discuss the parameterization of $\tilde{N}$, $\kappa_\ell$, and $\psi^e_\ell$. I use log-linear specifications in demographic conditions $d$ to estimate $\tilde{N}$ and $\kappa_\ell$:

$$\tilde{N}(d) = \exp(\theta_{\tilde{N}_o} + \theta_{\tilde{N}_d}d)$$  \hspace{1cm} (2.16a)$$

$$\kappa_\ell(d) = \exp(\theta_{\kappa_\ell} + \theta_{\kappa_d}d)$$  \hspace{1cm} (2.16b)$$

For the sunk cost of entry $\psi^e_\ell$, I use a log-linear specification in regulatory conditions $r$:

$$\psi^e_\ell(r) = \exp(\theta_{\psi_o} + \theta_{\psi_r}r)$$  \hspace{1cm} (2.17)$$

For the sake of tractability, I discretize all persistent state variables (the neighbourhood attributes $d_m$ and the regulatory stringency $r_m$ into five evenly spaced bins. When estimating the transition rates in Equation 2.12, I smooth across bins using a multidimensional Gaussian kernel with optimal bandwidth. I set the future discount parameter $\delta$ at 0.9 per year\(^{12}\). I calculate the standard errors from the score function of the likelihood.

### 2.2.4 Identification of colocation benefits

The model outlined above ascribes differences in venue entry and exit rates as a function of other venues in the neighbourhood (holding constant regulation, demographic attributes, and the build environment) to consumer preferences for variety. This may initially seem to be a strong assumption as in general firms in the same industry may benefit from colocation for reasons other than consumer preferences. However, consumer preferences for variety are likely to be particularly strong in the context of the nightlife industry. Moreover, I argue that other sources of agglomerative benefits are unlikely to be as important here as in other

\(^{12}\)The assumption of a constant discount rate follows the convention in the literature. Other studies which assume a constant discount rate of 0.9, 0.925, or 0.95 to estimate a dynamic structural model include Aguirregabiria and Mira (2007), Bajari, Benkard and Levin (2007), Ryan (2012), Collard-Wexler (2013), Dunne et al. (2013). As Magnac and Thesmar (2002) note, the discount factor is generally not well-identified in dynamic discrete choice models.
industries.

One immediate alternative hypothesis is that venues may gain some production cost advantage to colocation. However, as noted by Samadi (2012), the average nightlife venue’s costs are unlikely to vary significantly within a city. Specifically, the average venue’s spending on wages, alcohol purchases, and utilities constitutes 70.0% of its total spending. (The remainder is accounted for by depreciation and other expenses.) While alcohol purchases (which account for 45.6% of spending) may seem to offer possible cost advantages if distributors offer discounts to nearby venues, this does not appear to be the case. Wirtz Beverage Illinois (one of the largest distributors in Chicago) makes deliveries within the city limits based on a flat minimum order Wirtz Beverage Illinois (n.d.).

An alternative explanation for colocation studied by Toivanen and Waterson (2005), Yang (2013), and Shen and Xiao (2014) is that firms learn about the profitability of a given location by observing each others’ success. However, these studies generally consider learning effects for firms seeking to open in new cities. Learning seems as though it would be less of a concern in the current context. Most venues are owned by a firm that owns no other venues; insofar as the owners of these firms are likely to be located in Chicago, their knowledge of local conditions is likely strong\textsuperscript{13}. The cost of acquiring information is likely relatively low in Chicago, which is a very large and prominent city with well-documented distinct neighbourhoods. Moreover, as shown in Figure 2.3, the spatial distribution of venues covers the densely populated areas of the city. Accordingly, the ability to learn about very local conditions from other venues’ experiences appears to be fairly well-distributed across the city.

Holmes (2011), Arcidiacono et al. (2012), Igami and Yang (2014), and others have discussed the role of strategic siting by retail chains as a possible explanation for observed firm location patterns. However, this would not seem to be relevant in the current context. As discussed in further detail below, concentration in the nightlife industry in Chicago is very low. The overwhelming majority of venue licenses are held by firms which hold no other venue licenses.

\textsuperscript{13}Chinco and Mayer (2014) provide evidence for strong informational advantage of local investors in the housing market.
As Datta and Sudhir (2013) note, failing to account for local heterogeneity and zoning leads to misspecification errors. These may overstate the importance of agglomerative effects. However, in this paper, I account for neighbourhood heterogeneity and regulatory conditions directly.

In the context of nightlife specifically, consumer demand may be higher in neighbourhoods with more foot traffic or higher-quality commercial districts. These unobservable neighbourhood attributes could lead to colocation of venues, which the model would misattribute to consumer preference for variety. I address this possibility directly as a robustness check using the locations of Starbucks coffee shops as a proxy for these unobservable neighbourhood attributes. I find no evidence of a systematic relationship between Starbucks locations and nightlife venue profitability.

Accordingly, it seems reasonable to attribute the effect of the number of competitors on firm profitability to consumers’ preference for variety. Not only is consumer preference for variety likely to be particularly relevant in the nightlife industry (where consumers prefer the ability to visit several venues with low travel cost) but also the other potential agglomerative effects on firm profitability seem less significant.

### 2.3 Data and industry details

To estimate the structural model outlined above, I use data from Chicago. To explain how the data set corresponds with the model outlined above, I discuss the specific conditions of the Chicago nightlife industry in some detail.

#### 2.3.1 Nightlife venues

For information on nightlife venues, I use business license data from the City of Chicago Data Portal, which provides information on the new, renewed, and expired business licenses from January 2006 through July 2014. Representative examples of nightlife venues in my sample include “Ted’s Firewater Saloon”, “Los Globos Ballroom”, and “Zero Degrees Karaoke Bar”. I assume that a new liquor license represents a new entrant while an expired liquor license represents an incumbent exiting the market. This data set contains information
on liquor licenses (both for establishments which primarily serve alcoholic beverages and establishments with “incidental” consumption of alcohol) as well as an indication of whether the licensee’s operations including music or dance and an indication of whether the licensee is a “Public Place of Amusement”. (Public Places of Amusement include theatres, concert halls, bowling alleys, pool halls, karaoke bars, and arcades as well as nightclubs and similar facilities (Chicago City Council, 1990a).)

In this study I examine consumer’s preference for variety among similar venues as well as their preference across different types of venues. I use characteristics of venues’ business licenses to assign them to separate sectors. Business license attributes delineate the following four categories of nightlife venues:

- Venues which have Public Place of Amusement licenses with either no liquor licenses or licenses only for “incidental” consumption (“Amusement only”)
- Venues with alcohol licenses which do have Public Place of Amusement licenses and which do not have music/dance licenses (“Drinks only”)
- Venues with alcohol licenses and Public Place of Amusement licenses but not music and dance licenses (“Drinks and amusement”)
- Venues with alcohol licenses and music/dance licenses and possibly also Public Place of Amusement licenses (“Drinks and music”)

I compare these venue categories to venue categories listed on Yelp and find that the business license categories are strongly predictive of the Yelp categories. (Appendix C contains details of this comparison.) While the data set includes restaurants and mobile food vendors, I do not include these categories in the estimation. Restaurants may not contribute as strongly to nightlife amenities and they are frequently owned by chains which may optimize according to a very different strategy than the one described above. I am unable to sensibly assign mobile food vendors to a particular neighbourhood due to their mobile nature.

Figure 2.3 shows the geographical distribution for venues across Chicago. As shown, all venue types are widely distributed across the city. Table 2.1 shows summary statistics.
for the venues in the sample. Relatively few venues are present for the entire sample. For example, of the 794 “Drinks only” venues, only 22 survive the sample while 408 enter and then exit during the sample period. This is consistent with the high exit rates for new venues documented by Abbring and Campbell (2005) and provides sufficient variation in entry and exit rates to estimate the model outlined above.

Figure 2.4 shows the distribution of durations in the sample for each type. As shown, venues of the “Drinks and music” type tend to have the longest durations within the sample, to the extent that they almost strictly first-order stochastically dominate all other venue types’ duration. Conversely, the sample durations for the “Amusement only” are almost first-order stochastically dominated by all other venue types. However, each venue type has significant variation in sample duration.
It is worth emphasizing that the licensing data set suggests the industry has a very low level of concentration. With fewer than a dozen exceptions (e.g. multiple Four Seasons hotels with their own bars) the license for each venue is held by a different firm. Matching firm names for licenses in the data set gives a Herfindahl index of 0.00694. This is consistent with the description of Samadi (2012), who describes the market share concentration as “low” and notes that the nightlife industry “in general, consists of small businesses, with
few major operators and many being family owned and operated\textsuperscript{14}. Therefore, it seems reasonable to treat the individual venue as the decision-making unit.

\subsection*{2.3.2 Neighbourhoods}

To discretize the city into separate nightlife markets, I use the community area boundaries developed by the University of Chicago’s Local Community Research Committee in the 1920s to provide a more salient alternative to census tracts (Seligman, 2004). Inevitably, any partition scheme for discretizing a city into neighbourhoods is somewhat artificial. However, these neighbourhood boundaries appear to provide a reasonable approximation to actual geographical segmentation of the market for nightlife venues. Not only are these boundaries used for city planning and public service (e.g., the Chicago Neighbourhood Stabilization housing market program organizes its activities by neighbourhood), but they are also frequently used in real estate listings as well as media reports comparing Chicago neighbourhoods and therefore likely reflect popular usage (Rodkin, 2010; Taylor, 2013; Moser, 2013). Accordingly, in terms of spatial units which consumers and venues might use, community areas seem like a reasonable choice. Many authors in various public policy literatures have also adopted the community area as a unit of analysis (Wilson and Daly, 1997; Shah, Whitman and Silva, 2006; Illinois Assisted Housing Action Research Project, 2010).

These neighbourhood boundaries imply that in this model consumers gain no variety from venues outside a given neighbourhood, no matter how close they are to the boundaries. This would appear to be a strong assumption on the model. However, practically speaking, the neighbourhood boundaries appear to capture areas in which the local density of venues is relatively uniform. Figure 2.5 compares the normalized standard deviation of distance to the $k^{th}$ nearest neighbour venue for $k$ from 1 to 10. As shown, the normalized standard deviation is much lower within neighbourhood than between neighbourhood, particularly when $k \geq 3$.

\textsuperscript{14}It appears that this low concentration is broadly representative of other large cities. While none offer a panel of similar length to the Chicago data, the business license data set for currently-operating businesses in the category “Drinking places (alcoholic beverages)” from San Francisco Data suggests a Herfindahl index of 0.0146 while the 2012 business license data set from data.seattle.gov for business in the category “Drinking places (alcoholic beverages)” suggests a Herfindahl index of 0.0108. These values are higher than the very low concentration in Chicago, but still reflect an industry composed of many small firms.
Figure 2.5: Comparison of variation in nearest-neighbour differences within and between
neighbourhoods. The abbreviation “N.s.d” refers to the normalized standard deviation —
that is, the standard deviation divided by the mean. The abbreviation “n.n” refers to the
nearest neighbour. Each label $k$ denotes the normalized standard deviation for the distance
to the $k^{th}$ nearest neighbour. This figure only includes venues in the sample at the end of
the sample period. However, results are similar at other points in the sample period.

Therefore, despite the possibility of nearby venues in other neighbourhoods, it appears that
consumer access to variety is relatively constant across all venues in a given neighbourhood
compared to the difference in consumer access to variety across neighbourhoods.

Moreover, reduced-form regression results suggest that within-neighbourhood neigh-
bouring venues have less meaningful effects on entry and exit rates. For each of the four
venue types, I estimate three Cox proportional-hazards regression models for the entry and
exit rates with the following controls:

1. The first four principal components of neighbourhood attributes and the share of the
   neighbourhood covered by dry areas and moratoria (as discussed below and as shown
   in Figure 2.6)

2. All the controls from the previous regression as well as the number of venues of each
<table>
<thead>
<tr>
<th>Entry/Exit</th>
<th>Amusement only</th>
<th>Drinks only</th>
<th>Drinks and amusement</th>
<th>Drinks and music</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entry</td>
<td>19.50***</td>
<td>1.64</td>
<td>43.79***</td>
<td>15.64***</td>
</tr>
<tr>
<td></td>
<td>20.98***</td>
<td>1.55</td>
<td>24.76***</td>
<td>6.80*</td>
</tr>
<tr>
<td>Exit</td>
<td>21.78***</td>
<td>0.81</td>
<td>69.62***</td>
<td>15.05***</td>
</tr>
<tr>
<td></td>
<td>9.11*</td>
<td>6.21</td>
<td>22.21***</td>
<td>1.36</td>
</tr>
</tbody>
</table>

Table 2.2: Likelihood ratio tests for Cox proportional hazard survival models of venue entry and exit. The first column adds controls for the number of venues of each type in the same neighbourhood. The second column adds controls for the number of venues of each type in neighbouring neighbourhoods (weighted by the length of shared border between neighbourhoods). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

3. All the controls from the previous regression as well as the number of venues of each type in neighbouring neighbourhoods (weighted by the length of the shared boundary)

The third model nests the second model, which in turn nests the first model. Accordingly, it is possible to compare models using the likelihood ratio. Table 2.2 shows the likelihood ratio comparisons. As shown, the likelihood ratio is highly statistically significant in all cases when controls for venues in the same neighbourhood are added. However, the likelihood ratio between models with and without controls for venues in neighbouring neighbourhoods are always much smaller and (with the exception of “Drinks only” venues) not statistically significant. This indicates that the community area boundaries provide a practical strategy for market delineation that in most cases captures the variation with substantial impact on venues’ entry and exit decisions.

Below, I explore alternate definitions of neighbourhood boundaries as a robustness check. I find that results for consumer preference for variety are not sensitive to the specific boundaries between neighbourhoods.
2.3.3 Regulatory environment

Venues in Chicago face citywide regulatory barriers to entry as well as very local within-city regulation. Citywide regulatory barriers include a licensing fee of at least $4,400 (with additional fees for patios and later hours of operation) and applications for new licenses must include extensive documentation as well as liquor liability insurance and criminal background checks for investors, corporate officers, and managers (Chicago Department of Business Affairs and Consumer Protection, n.d.). These represent significant sunk investment costs, particularly since liquor license applications are sometimes rejected (Kindelsperger, 2011; Maidenberg, 2013; Morgan, 2013) and therefore investors may be reluctant to contribute to opening a new venue. Moreover, the regulatory process may introduce unpredictable and potentially costly delays to the process.

At the local level, Chicago has a distinct system of liquor license regulation which features two forms of restriction on liquor licensing: bans and moratoria (Chicago Department of Business Affairs and Consumer Protection, n.d.). Bans prohibit outright the issuance of liquor licenses; all incumbent venues must exit when a new ban is enacted. Moratoria place restrictions on the locations of new primary liquor licenses — most importantly, a moratorium sets a minimum distance from existing primary liquor licenses.

Bans are instituted by popular vote in precinct-level referenda which take place alongside other elections (Illinois General Assembly, 1934). The legislation to empower voters to enact outright bans on liquor licenses was enacted in 1934 immediately after the end of Prohibition, when many state legislatures were granting local control over liquor purchase and consumption (Strumpf and Oberholzer-Gee, 2000). In the modern context, these referenda are unique to Chicago among large American cities. The precincts are the lowest level of political division in Chicago and therefore these referenda are very local. In the forty referenda since 2000, the total ballot count has averaged 241, and none has returned more than 490 ballots. The ban can be repealed, but it seems this rarely occurs. Only one of the forty referenda since 2000 considered a potential repeal, and this referendum was defeated.

It appears that venues regard the referendum process as beyond their ability to influence. Incumbent venues affected by dry precinct bans tend to accept a referendum once it is
announced (Cawthon, 1998; Mitchell, Moore and Yousef, 2011; Byrne, 2012). Potential entrants are often deterred very early in the entry process by potential referenda regardless of support from local politicians and institutions (Lambert, 2008; Mitchum, 2008; Lam, 2008). These media reports suggest that venue owners regard attempts to influence proceedings as ineffective.

Liquor license moratoria are established by decisions of city council (Chicago City Council, 1990b). Moratoria also impact liquor license at a very local scale; some moratoria apply only to one side of a particular street. Within a moratorium zone, new liquor licenses are prohibited within 400 feet of existing licenses. Existing licenses may only be transferred to immediate family members, business partners, or inheritors. If a previously-licensed site loses its license, any attempt to open a new venue on the same premises faces steep regulatory hurdles, including the written consent of the majority of registered voters within a 500-foot radius. Accordingly, the license moratorium drastically increases the cost of market entry.

The City of Chicago Data Portal provides information on the locations of dry precincts and local moratoria. The local shares of dry precincts and local moratoria change only slightly over the sample period (predominantly in a few already heavily-regulated neighbourhoods with few venues). Accordingly, I use the average level of regulatory stringency over the sample period. While time-varying regulatory stringency would be possible in this empirical framework, including variation in regulation substantially would increase the size of the state space while providing minimal additional information about venues’ decisions.

In addition to the moratoria and dry precincts, municipal noise regulations prohibit liquor licenses within 100 feet of schools, libraries, churches, and certain categories of businesses (Chicago City Council, 1990c). The City of Chicago Data Portal provides information on the locations of schools and libraries, as well as the list of institutions given exemptions from water charges. I infer the locations of churches and similar religious edifices from the names of institutions granted exemptions\textsuperscript{15}. As these restrictions are virtually indistinguishable from the dry precincts, I include these with dry precincts as a single form of

\textsuperscript{15}In particular, I assume that any institution granted an exemption with “church”, “temple”, “masjid”, “synagogue”, “mosque”, “tabernacle”, or a similar term in its name is a religious edifice near which new liquor licenses are prohibited.
Figures 2.6a and 2.6b show the proportion of each neighbourhood covered by liquor license moratoria and dry areas. Most neighbourhoods are less than 5% covered by moratoria, while several are over 50% covered by dry precincts.

In this study, I construct a model which captures the effects of these regulations on nightlife venues. Precinct-level bans and license moratoria reduce the available real estate for nightlife venues and therefore make it more difficult to find a venue site. In the model, this raises the cost of entry for potential entrants. Moreover, the presence of positive effects of venue colocation on profit complicates the dynamic response of industry to any given policy change; if more stringent policy causes some venues to exit the market, nearby venues benefit from the reduced competition but also may lose customers due to reduced density of nearby venues.

2.3.4 Neighbourhood attributes

Local demographic and infrastructure characteristics may impact venue profitability. To account for this, I obtain tract-level data from the 2010 US Census as well as demographic data from the 1% sample of the American Community Survey (ACS) through the IPUMS database (Ruggles et al., 2010). The ACS data contains geographic specification to the level of the Public Use Microdata Area (PUMA), which is a Census designation for a geographical region of approximately 100,000 residents. I match the tract-level and PUMA-level data to the community areas using GIS software. Table 2.3 shows summary statistics for neighbourhood attributes.

Ideally, the estimation would condition on all these variables. However, this would substantially increase the dimensionality of the state space and create a challenge for the numerical algorithms used for likelihood maximization. Moreover, many of these neighbourhood attributes are closely correlated. I address this by considering four principal components of the data. Table 2.4 shows the loading factors for the four principal components. These four components collectively explain 93% of the variance between neighbourhoods. The remaining components account for a much smaller share of the variance. The first principal component primarily corresponds to dense areas near the central business district while the
Table 2.3: Summary statistics for the 77 neighbourhoods in the sample. The last two rows are regulatory variables which are not included in the principal component analysis but rather included directly.

second principal component primarily corresponds to poorer and less dense areas further from the city centre. The neighbourhood attributes are summarized graphically in Figure 2.6.

2.4 Results and discussion

In the discussion of the empirical results, I focus on consumer preferences for variety and the parameters determining venues’ entry and exit decisions. Appendix D shows the full set of estimated parameter values including the impacts of demographic attributes on the parameters of the profit function. Figure 2.7 shows the first-stage nonparametric entry and exit rates $\hat{h}_e^c$ and $\hat{h}_x^c$ on which the structural estimates are based. As shown, all venue types have a wide range of entry and exit rates across states. I calculate the standard errors for the results in Figure 2.7 using the Nadaraya-Watson asymptotic variance for the nonparametric entry and exit rates. As shown, the entry and exit rate estimates appear to be quite precise.
Table 2.4: Factor loadings for principal component analysis together with the cumulative share of variance explained by the principal components.

<table>
<thead>
<tr>
<th>Principal component</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age 20–34 (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonfamily (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH with children (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Renters (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>African-American (%)</td>
<td>-0.459</td>
<td>-0.654</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latino/Hispanic (%)</td>
<td>0.409</td>
<td>0.316</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income (\leq 25k) (%)</td>
<td>0.229</td>
<td>-0.107</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income (\geq 100k) (%)</td>
<td>-0.181</td>
<td>0.17</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty (%)</td>
<td></td>
<td></td>
<td>0.213</td>
<td></td>
</tr>
<tr>
<td>Detached housing (%)</td>
<td>-0.197</td>
<td>-0.235</td>
<td>0.126</td>
<td></td>
</tr>
<tr>
<td>&gt; 50 unit housing (%)</td>
<td>0.12</td>
<td></td>
<td>0.228</td>
<td></td>
</tr>
<tr>
<td>Pre-1990 housing (%)</td>
<td></td>
<td></td>
<td>-0.124</td>
<td></td>
</tr>
<tr>
<td>HH income ($1000)</td>
<td>0.112</td>
<td>-0.647</td>
<td>0.567</td>
<td></td>
</tr>
<tr>
<td>Transit stations</td>
<td>0.961</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pop. dens. (km(^2))</td>
<td></td>
<td>-0.988</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cum. share of variance</td>
<td>0.444</td>
<td>0.763</td>
<td>0.863</td>
<td>0.932</td>
</tr>
</tbody>
</table>

Table 2.5: Maximum likelihood estimation results for the CES parameters \(\eta\) and \(\rho_\ell\). Standard errors in parentheses.

<table>
<thead>
<tr>
<th>Elasticity</th>
<th>Symbol</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between sectors</td>
<td>(\eta)</td>
<td>2.04 (0.002)</td>
</tr>
<tr>
<td>Amusement only</td>
<td>(\rho_1)</td>
<td>4.90 (0.013)</td>
</tr>
<tr>
<td>Drinks only</td>
<td>(\rho_2)</td>
<td>2.15 (0.001)</td>
</tr>
<tr>
<td>Drinks and amusement</td>
<td>(\rho_3)</td>
<td>3.56 (0.224)</td>
</tr>
<tr>
<td>Drinks and music</td>
<td>(\rho_4)</td>
<td>7.96 (0.290)</td>
</tr>
</tbody>
</table>

Table 2.5: Maximum likelihood estimation results for the CES parameters \(\eta\) and \(\rho_\ell\). Standard errors in parentheses.

### 2.4.1 Parameter estimates

Table 2.5 shows the estimated CES parameters for consumer preference across venues. As shown, the elasticity of substitution between sectors \(\eta\) is very low, which indicates a strong preference for variety between sectors. The elasticity of substitution within sectors varies widely. Consumers have a particularly strong preference for variety among “Drinks only” venues (e.g., bars without live music and taverns) and a less-strong preference for variety among “Drinks and music” venues (e.g., bars with live music and performance venues).
(a) Share of area dry (%)
(b) Share of area moratorium (%)
(c) First principal component
(d) Second principal component
(e) Third principal component
(f) Fourth principal component

Figure 2.6: Neighbourhood attributes.

Insofar as I estimate these results based on a CES utility function, they are broadly comparable with other results in the international trade and urban literatures that examine consumer preference for variety\textsuperscript{16}. The estimate for the constant elasticities of substitution

\textsuperscript{16}However, as noted previously, the consumers’ reservation shock is novel to this model and therefore the
Figure 2.7: First-stage results for venue entry and exit rates as a function of state. Units are days$^{-1}$ throughout. Error bars in grey represent one standard deviation.

The entry rate of “Drinks and music” venues is close to the elasticity of substitution in the range of 8.4–8.8 for restaurants reported by Couture (2014). Meanwhile, the elasticity of substitution between “Drinks only” venues is very low — the value of 2.15 is below the first percentile of goods reported in Broda and Weinstein (2010) and comparable to the elasticity of substitution between varieties for highly variety-specific goods such as coffee, automotive parts, and footwear in Broda and Weinstein (2006). The elasticities of substitution for the other two venue types are more comparable to the 5th to 25th percentile of elasticities for consumer goods reported in Broda and Weinstein (2010).

These results suggest a strong preference for variety in nightlife compared to other consumption goods and services, particularly among bars, taverns, and similar venues without music, dancing, or other amusement. (Below, I quantify this preference by assessing the marginal impact of a new venue on consumer welfare.) This strong preference for variety may indicate a consumer preference for the ability to “bar-hop” between many venues of interpretation of these elasticities is not precisely identical to others in the literature.
<table>
<thead>
<tr>
<th>Move arrival rate</th>
<th>Symbol</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amusement only</td>
<td>$\alpha_1$</td>
<td>4.00 (0.01)</td>
</tr>
<tr>
<td>Drinks only</td>
<td>$\alpha_2$</td>
<td>905 (98)</td>
</tr>
<tr>
<td>Drinks and amusement</td>
<td>$\alpha_3$</td>
<td>718 (86)</td>
</tr>
<tr>
<td>Drinks and music</td>
<td>$\alpha_4$</td>
<td>14.8 (24.3)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Entry</th>
<th>Exit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amusement only</td>
<td>$\lambda_1$</td>
</tr>
<tr>
<td>Drinks only</td>
<td>$\lambda_2$</td>
</tr>
<tr>
<td>Drinks and amusement</td>
<td>$\lambda_3$</td>
</tr>
<tr>
<td>Drinks and music</td>
<td>$\lambda_4$</td>
</tr>
</tbody>
</table>

Table 2.6: Maximum likelihood estimation results for the move arrival rate parameters $\alpha_\ell$ and $\lambda_\ell$. All values are measured in $10^{-3}$ days$^{-1}$. Standard errors in parentheses.

this type. As well, this may reflect an ability by venues without music and and dance licenses or Public Place of Amusement licenses to differentiate themselves in some other unobservable attributes (e.g. décor or types of beverages offered).

Table 2.6 shows the arrival rates for agents to enter and exit the market. Entry opportunities arise most frequently for the “Drinks only” sector, followed closely by the “Drinks and amusement sector”. The other sectors experience fewer opportunities to enter the market. Meanwhile, incumbent venues face opportunities to exit the market at a low frequency (on the order of once per year) across all sectors. This may reflect the timescale of leases, supplier agreements, or other contractual obligations, or it may reflect a low rate of arrival for preferable outside opportunities for nightlife venue operators.

In the dynamic model, the sunk cost of entry and the payoff of exit consist of a deterministic component plus a stochastic component. Table 2.7 shows the estimated values for the logarithm of the deterministic component of the sunk cost and the exit payoff. These values are denominated in model units. I convert to dollar values below. As shown, the barriers to entry are quite high compared to the payoff from exit.

In Table 2.7, I also report the effect of dry precincts and moratoria on the barriers
to entry. As I estimate the deterministic component of the barrier to entry as a log-linear function of the prevalence of regulation, these should be interpreted as elasticities. Specifically, a 1% increase in dry precincts in a neighbourhood raises the barrier to entry by 0.47% while a 1% increase in moratoria in a neighbourhood raises the barrier to entry by 0.11%. As shown in Figure 2.6a, some neighbourhoods are over 60% dry precincts; therefore the estimation results suggest that this poses a substantial deterrent to entry.

The estimated parameter values imply a payoff from exit much lower than the sunk cost of entry. This may partially be explained by the non-transferability of liquor licenses. Licensing regulation allows for a nightlife venue to be sold, but it does not allow for a new operator to use the license for a location that previously hosted a nightlife venue but exited the market (Chicago City Council, 1990). Accordingly, a nightlife venue operator cannot recoup the significant costs associated with the licensing process upon exiting the market. An exiting nightlife venue operator is also unlikely to be able to recover the cost of the structural renovations which were necessary to open a new nightlife venue. As discussed below, the costs of building improvements can be substantial.

These estimated parameters are all in terms of model units, which are determined by the normalization condition on the reservation utility shock \( \max \{V^*\} \equiv 1 \). To understand these parameter values in terms of policy implications, it is useful to express these terms in dollar values. According to Samadi (2012), the average revenue for a nightlife venue in the United States is $345,121 annually. I assume that this value is representative for venues which only serve drinks, which is the most-numerous venue category in the sample and which seems likely to be most representative of the national average. As well, I assume that 3.6% of revenue is profit as suggested in Samadi (2012) is a representative value for my sample. This suggests a profit of $12,424 annually\(^{17}\). Given the discount factor of 0.9 per year, this indicates that (in a hypothetical steady-state environment) the net present value of an incumbent venue is on the order of $124,240. The median continuation value across all states for “Drinks only” venues is 1.24. Therefore, one model unit is approximately $99,810.

\(^{17}\)Specifically, Samadi (2012) notes that profit margins can be as high as 59.7% of revenue, but 3.6% is the average. This broad dispersion suggests that any dollar values should be interpreted as generally indicative rather than as precise estimates.
### Table 2.7: Maximum likelihood estimation results for the logarithm of deterministic component of the sunk cost of entry and the exit payoff. The “baseline” entry cost reflects the entry cost in the absence of local regulation. Standard errors in parentheses.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter Estimate (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Entry cost</strong></td>
<td></td>
</tr>
<tr>
<td>Amusement only baseline</td>
<td>2.11 (0.003)</td>
</tr>
<tr>
<td>Drinks only baseline</td>
<td>2.17 (0.008)</td>
</tr>
<tr>
<td>Drinks and amusement baseline</td>
<td>2.11 (0.02)</td>
</tr>
<tr>
<td>Drinks and music baseline</td>
<td>1.81 (0.25)</td>
</tr>
<tr>
<td>Role of dry precincts</td>
<td>0.470 (0.003)</td>
</tr>
<tr>
<td>Role of moratoria</td>
<td>0.106 (0.03)</td>
</tr>
<tr>
<td><strong>Exit payoff</strong></td>
<td></td>
</tr>
<tr>
<td>Amusement only</td>
<td>-4.01 (0.82)</td>
</tr>
<tr>
<td>Drinks only</td>
<td>-4.06 (0.06)</td>
</tr>
<tr>
<td>Drinks and amusement</td>
<td>-2.76 (0.32)</td>
</tr>
<tr>
<td>Drinks and music</td>
<td>-3.23 (0.07)</td>
</tr>
</tbody>
</table>

As a strategy for verifying the conversion factor from model units to dollars, I consider the cost of purchasing an operating venue. This cost should be comparable to the net present value of an incumbent venue. I use data from BusinessBroker.Net (n.d.) to obtain the price for purchasing an incumbent nightlife venue. While this data includes only the asking price rather than the purchase price, it provides some indication of the net present value of a nightlife venue. This data source contains relatively few Chicago-specific venues; as of writing, only one nightlife venue is listed in Cook County for an asking price of $150,000. Therefore, I consider all businesses listed in the “Food & Beverage: Bars, Clubs, Nightspots” category which include the term “bar”, “pub”, “club”, “tavern”, or “lounge” in the description but exclude “restaurant”. The median price in this sample is $250,000 with an interquartile range of [$150,000,$250,000]. Insofar as these are asking prices rather than price received by the seller and this illiquid market is likely prone to negotiation these values may overstate the market value somewhat. Together with the single observation of
a $150,000 asking price in Chicago, this lends some plausibility to the net present value conversion factor of $124,240.

This conversion factor allows me to assign dollar values for the sunk cost of entry and the payoff from exit. I use the parameter estimates from Table 2.7 to find the deterministic component and then add the median value of the stochastic component\(^{18}\) then convert from model units to dollars using the factor suggested by the results in Samadi (2012). Table 2.8 shows the resulting estimates. In general, the parameter estimates suggest barriers to entry on the order of several hundred thousand dollars. These are high barriers to entry which represent several years’ profit in most cases. Accordingly, potential entrants likely only choose to enter when they receive a particularly favourable value for the stochastic component of the sunk cost of entry\(^{19}\). These results suggest that barriers to entry may significantly reduce the variety offered to the consumer.

Table 2.7 includes confidence intervals for each of these estimates. I calculate confidence intervals using a Monte Carlo process. I re-draw one thousand parameter vectors from a normal distribution with the estimated parameters as its mean and the estimated variance matrix as its variance. Then, I re-calculate the median entry costs and exit payoffs under each of these re-drawn parameter vectors. I use the resulting distribution of median entry costs and exit payoffs to form confidence intervals.

As noted previously, the payoff upon exit is substantially lower than the sunk cost of entry. However, the parameter estimates suggest a deterministic component of the exit payoff that is small compared to the stochastic component. Therefore, depending on the realization of the stochastic components, venues facing an opportunity to exit face a range of possible realizations of the exit payoff shock.

Abbring and Campbell (2005) find that the value of a nightlife venue in its first year of

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\(^{18}\)Given the extreme-value functional form of the shocks, the median value of the stochastic component is \(-\log \log 2\).

\(^{19}\)However, while these values appear high, they are comparable in magnitude to costs discussed in the non-academic business literature. Ingram (n.d.) suggests initial improvements to the building when opening a nightclub cost $18,000 to $65,000, sound equipment can cost $50,000 to $300,000, and the lease for the facilities will generally exceed $10 per square foot. As well, Ingram (n.d.) notes that the total cost of acquiring a liquor license can range as high as $1 million depending on the jurisdiction. As noted previously, venues in Chicago face an extensive regulatory process which includes licensing and application fees as well as extensive documentation requirements. Fullbright (n.d.) gives a “low-end estimate” of the cost to start a nightclub of $239,250 and a “high-end estimate” of $837,100. Samadi (2012) suggests the cost of opening a venue ranges from $100,000 to $200,000 to $1 million or more, depending on venue size.
Table 2.8: Estimated sunk cost of entry. 95% confidence intervals in parentheses.

<table>
<thead>
<tr>
<th>Entry cost</th>
<th>Value (thousands of dollars)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amusement only baseline</td>
<td>862</td>
</tr>
<tr>
<td>Drinks only baseline</td>
<td>943</td>
</tr>
<tr>
<td>Drinks and amusement baseline</td>
<td>892</td>
</tr>
<tr>
<td>Drinks and music baseline</td>
<td>670</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Exit payoff</th>
<th>Value (thousands of dollars)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amusement only</td>
<td>38.4</td>
</tr>
<tr>
<td>Drinks only</td>
<td>38.3</td>
</tr>
<tr>
<td>Drinks and amusement</td>
<td>42.9</td>
</tr>
<tr>
<td>Drinks and music</td>
<td>40.5</td>
</tr>
</tbody>
</table>

operation lies mostly in its potential to exit the market; their structural estimates indicate that the payoff from exit is 124% the continuation value of a firm in its first year of operation. Conversely, my estimates suggest that for a “Drinks only” venue that has just entered the market that has just entered the market, the payoff from exit is 35.5% of the continuation value. While still substantial, this result is much lower than the Abbring and Campbell (2005) estimate. The discrepancy may arise from differences in the attribution of fixed costs. While my model includes an initial sunk cost immediately upon entry and a constant fixed cost thereafter, Abbring and Campbell (2005) account for the cost of entry by allowing fixed cost to vary over time and therefore their model yields a lower continuation value early in the firm’s operation as the cost of entry is effectively being subtracted from the flow of profit.

2.4.2 Goodness of fit

In interpreting these results, it is worth examining how well the model’s predictions match observed data. As a check on the model’s goodness of fit, I use the estimated parameter values to solve for the equilibrium via value function iteration then compare the wait times between transitions (i.e., venue entry or exit) as predicted by the model to the wait times
between transitions as actually observed. Recall that the parameters are set by maximizing the joint likelihood of the wait time between transitions and the type of transition — i.e., whether it is an entry or an exit and which type of venue is entering or exiting. The goodness-of-fit measure described here only accounts for the former. Insofar as the arrival of each venue’s move in a given state is equivalent to the arrival time of a Poisson process, this measure reflects the total intensity of the collection of Poisson processes in a given state.

This measure indicates reasonably close fit; the correlation between observed and predicted wait times is 0.322. Averaging over observations with the same number of incumbents of each type $n_m$ (but different demographics $d_m$ and regulation $r_m$) gives a correlation of 0.479. Both of these values are highly statistically significant. Figure 2.8 plots the observed and predicted wait times between state transitions. The observed and predicted values are clearly positively correlated. The model has some tendency to overestimate the frequency of state transitions; most of the time, this occurs because the model predicts more rapid exit of venues than actually observed.

It is worth discussing which aspects of the model might influence its ability to closely fit the data. The dynamic model of venue entry and exit involves several restrictions which are necessary for computational tractability or identification but which necessarily reduce the flexibility. As mentioned previously, I assume that venues discount the future at the constant rate $\delta = 0.9$. While this follows the standard approach in the literature, it may be a poor approximation to reality if a venue’s discount rate is driven by its cost of capital and that discount rate is substantially lower than 10%. In this context, the model could overpredict exit if an incumbent is more “patient” and chooses to continue operating in low-profit situations if other venues’ entry and exit decisions are likely to lead to higher profits in the future. Also, the assumption that the move arrival rates $\alpha_\ell$ and $\lambda_\ell$ are constant is necessary for the identification of venues’ entry and exit probabilities, but this may fail to account for cycles in local real estate markets or changes in landlords’ attitudes towards nightlife venues which may impact venues’ entry or exit decisions. The assumption that

\footnote{However, it is likely that nightlife venue operators face high borrowing costs. Ortiz-Molina and Penas (2008) present evidence that the average small-business line of credit has an interest rate on the order of 8%.}
the stochastic components of the entry cost and exit payoff are distributed according to an extreme value random variable may be a poor reflection to reality and may lead to an unrealistic incidence of “tail events” where entrants receive a very low entry cost or incumbents receive a very high exit payoff compared to reality.

The static model also includes several abstractions which allow for a closer focus on competition and consumer preferences for access to variety. Agents receive no labour income or non-pecuniary utility from operating a nightlife venue, although in the real world this may prevent venues with very low profit from taking exit opportunities. Also, there is no channel for entrepreneurs to learn additional information about market conditions or their own competence after entering the market; the decision to remain in the market is driven wholly by profit (as predicted by local demographics and presence of competition) and the arrival of exit opportunities.
2.4.3 Counterfactual scenarios

The estimation results above allow for the evaluation of counterfactual scenarios in both the static and dynamic context. I use it to evaluate the impact on consumer welfare and profits of the marginal venue entry in each neighbourhood as well as the dynamic impacts of changes to barriers to entry.

**Static counterfactuals**

Figure 2.9 shows the median changes in consumer welfare across all observations under scenarios where each neighbourhood gains a single venue of a given type $\ell$. These results account for changes to consumers who choose to go out as well as those who choose to consume their reservation utility. Recall that the reservation utility $V^*$ is uniformly distributed on the unit interval and that consumers will only consume their reservation utility if it is greater than the utility $V$ of going out. Therefore, the expected overall consumer welfare $W$ as a function of the utility of going out $V$ is as follows:

$$W(V) = \begin{cases} 
\frac{1}{2} + \frac{1}{2}V^2 & V < 1 \\
V & V \geq 1
\end{cases} \quad (2.18)$$

As shown in Figure 2.9, the South Side of Chicago is particularly underserved at current levels and welfare would increase substantially with additional venues of any type. Utility gains are particularly strong for “Amusement only” venues in the South Side and for “Drinks only” venues throughout the city. The median welfare gain from a new “Drinks only” venue is on the order of 13.5% while the median welfare gain for the other types is below 3%.

To interpret these welfare gains, it is helpful to express the welfare changes in terms of the magnitude of venue price reduction that would give consumers the same increase to utility. Since both prices and consumer budget $w$ are normalized by the entry cost, this is equivalent to the increase in $w$ that would give the same increase in utility. As shown in Equation 2.3, the utility $V(p)$ for consumers who choose to go out and consume nightlife services is proportional to $w$. (As shown in Equation 2.6, venue prices are independent...
Therefore, the compensating variation in $w$ (i.e., the change in $w$ that would give
consumers the same welfare gain as a new venue) is identical to the proportional change in
welfare shown in Figure 2.9.

It is worth emphasizing that this analysis of consumer welfare omits any potential neg-
ative externalities associated with nightlife venues. Dense concentrations of bars and clubs
are also associated with negative spatial externalities, including noise, crime, and litter
(Danner, 2003; Currid, 2007; Campo and Ryan, 2008; Darchen, 2013a) and nearby residents
and other businesses demand regulation to reduce the number of venues. These negative
externalities are beyond the scope of the model and therefore not included in the consumer
welfare results presented above. Accordingly, these results should not be interpreted as the

Figure 2.9: Changes to consumer welfare from one additional venue of each type. All
changes expressed as a percentage of the baseline welfare.

(a) Amusement only  (b) Drinks only
(c) Drinks and amusement  (d) Drinks and music

of $w$.) Therefore, the compensating variation in $w$ (i.e., the change in $w$ that would give
consumers the same welfare gain as a new venue) is identical to the proportional change in
welfare shown in Figure 2.9.

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and other businesses demand regulation to reduce the number of venues. These negative
externalities are beyond the scope of the model and therefore not included in the consumer
welfare results presented above. Accordingly, these results should not be interpreted as the
Table 2.9 summarizes the share of observations in which one (counterfactual) entrant of type $\ell'$ would increase profits for incumbents of type $\ell$ in the same neighbourhood. As shown, in a significant (albeit imprecisely estimated) share of observations, an additional venue would lead to enough additional demand to increase incumbent profit. Venues of the “Amusement only” and “Drinks and amusement” types have a high incidence of spillover to venues within the same type, while venues of the “Drinks only” type have a high incidence of spillover to venues of different types.

The presence of positive profit spillovers from new entrants may partially rationalize business improvement districts (BIDs). Business improvement districts exist to promote businesses in a specific neighbourhood. They are typically founded by the decision of a collection of nearby businesses to levy mandatory tax-like fees on all businesses in the district and use these fees to fund joint improvements and promotion (Briffault, 1999). Businesses have voted to create such districts specifically to promote entertainment and nightlife (Darchen, 2013b). This study’s results suggest that under some circumstances subsidizing nearby businesses can be increase profits. However, the formation of a business improvement district is not necessarily a Pareto improvement for its members. Brooks and Strange (2011) show that some firms oppose the formation of business improvement districts and many proposed districts fail to gain the necessary approval. When approved, property value benefits accrue
primarily to large anchor firms. The heterogeneous profit spillovers implied above are consistent with these results; new entrants would only improve profits for incumbents in some situations and the benefit varies widely with the type of incumbent and entrant venues.

As with the consumer welfare results, these results for nightlife profit do not necessarily represent the full equilibrium impact of the nightlife industry on the profits for all firms in the local economy. Insofar as nightlife venues occupy scarce retail real estate, they reduce the supply of storefronts available to other industries. Therefore, the opening of a new nightlife venue may disrupt similar benefits of colocation for other retail and service industries. In many parts of Chicago, available retail real estate is relatively constrained and it is reasonable to suppose that nightlife venues displace other economic activity. For example, in the River North and West Loop real estate submarkets, the vacancy rate in 2012 was 3.5%, while in the East Loop the vacancy rate was 2.2% (Bujwit, 2013). Without knowing which businesses are being displaced by nightlife venues and how those businesses benefit from access to variety, the impact of this externality on commercial real estate is unclear.

**Dynamic counterfactuals**

Next, I use the model to evaluate dynamic counterfactual scenarios. Throughout, I assume the stochastic form of the sunk cost shock and the exit payoff shock remain unchanged. Under each counterfactual, I re-solve the model using value function iteration under the counterfactual. Note that these counterfactual predictions also represent a Markov-Nash equilibrium; in the counterfactuals, agents have consistent beliefs regarding each others’ actions as a function of the current state.

First, consider a dynamic counterfactual where the deterministic component of the sunk cost of entry is exogenously lowered by 25% for all potential entrants in all neighbourhood. This change is approximately one standard deviation of the within-sample variation in entry cost. Figure 2.10 shows the net difference in annual venue entry rate — that is, the number of additional entries per year minus the number of additional exits per year under the counterfactual. As shown, the effects of lower barriers to entry are substantial. In some neighbourhoods, this would increase the rate of entry (relative to the final period of the
Figure 2.10: Changes to entry probability from lower entry cost. All changes expressed as the change in the rate of new entrants choosing to enter the market per year.

model) by five “Drinks only” venues per year and over 0.7 “Amusement only” and “Drinks and amusement” venues per year. The effects are largest on the South Side (which has a lower density of venues venues) and smallest in Central Chicago (which has a higher density of venues). This result suggests that policy changes to lower the entry costs could potentially lead to a drastic increase in the number of venues in neighbourhoods with relatively few venues. These results are dominated by increased entry; changes to the exit rates are smaller.

Next, consider a laissez-faire counterfactual where all local regulation (i.e., dry precincts and moratoria) are removed. Under this counterfactual, venues still face barriers to entry (due to startup costs and citywide regulation) but the cost is substantially lower. As shown
Figure 2.11: Changes to entry probability from laissez-faire local regulation. All changes expressed as the change in the rate of new entrants choosing to enter the market per year. Results for venues in the “Amusement only” category are not shown as venues without liquor licenses do not face local liquor regulation and the indirect effect from other venues’ higher entry rate is very small.

in Figures 2.6a and 2.6b, the impact of this counterfactual is largest in a few particularly heavily-regulated neighbourhoods. Figure 2.11 shows the change in entry rate under this scenario. As shown, the effect under the laissez-faire counterfactual is generally smaller than the effect under the counterfactual with across-the-board entry barrier reduction. To some extent, this may be because the heavily-regulated neighbourhoods tend to be the less-profitable neighbourhoods. At any rate, this counterfactual provides evidence that the high barriers to entry are not primarily driven by local liquor license restrictions (as opposed to municipal regulation or non-regulatory startup costs).
2.5 Robustness

To ensure that the model above is well-specified (and, in particular, to ensure that the effects attributed to $\eta$ and $\rho_l$ actually represent the effects on venue profit from consumer preferences for variety) I re-estimate the model under different specifications.

2.5.1 Cluster neighbourhoods

The results presented above use the community area boundaries developed by the University of Chicago’s Local Community Research Committee to define neighbourhoods. As discussed previously, these do not seem to be an unreasonable unit for discretization. Community areas have a reasonable size for nightlife consumers to travel within them, they are roughly convex, and in many cases they correspond with residents’ contemporary definition of neighbourhoods.

To ensure that these neighbourhoods correspond reasonably with nightlife consumers’ actual choice sets, I re-estimate the model using a definition of neighbourhoods based on the clustering algorithm introduced in Rozenfeld et al. (2011). I fix a spatial distance $d$, and use the algorithm to define a neighbourhood as the maximal spatial region in which no venue is at a distance greater than $d$ from any other venue. To ensure time-invariant neighbourhood boundaries, I include all sites at which a venue is ever observed in the sample. Let $V$ denote the set of all venues in the sample - then, the algorithm proceeds as follows:

- Choose a venue $v_o$ that is not yet assigned to a neighbourhood. Draw a circle of radius $d$ around venue $v_o$. Assign the set of venues $\{v' \in V \mid |v' - v_o| \leq d\}$ (that is the set of venues in the circle of radius $d$ around the venue $v_o$) to the same neighbourhood as $v_o$.

- For each newly-assigned venue $v'$ from Step 1, draw a new circle of radius $d$ and assign all not-yet-assigned venues to the same neighbourhood.

- Repeat Step 2 until the newly-drawn circles of radius $d$ no longer incorporate any new venues. The union of all circles from Steps 1 and 2 define a neighbourhood.
Repeat Steps 1 through 3 starting with a new unassigned venue to define new neighbourhoods until no unassigned venues remain.

At the end of this process, every venue is assigned to a neighbourhood. The resulting cluster neighbourhoods are independent of the starting point; each radius $d$ defines a unique set of neighbourhoods. Within each of these neighbourhoods, no venue is at any distance greater than $d$ from at least one other venue. Moreover, any venue within distance $d$ of a given venue is in the same neighbourhood.

For suitable values of $d$, this defines a neighbourhood as including the maximal set of venues that consumers could access in a single night. I consider $d = 250\text{m}$, $d = 500\text{m}$, and $d = 750\text{m}$ to give neighbourhoods of a comparable size to the community areas described above. Figure 2.12 shows the resulting cluster neighbourhoods for the case $d = 500\text{m}$. I re-estimate the model using these new neighbourhoods.

Table 2.10 shows the elasticity estimates under varying cluster sizes. As shown, the
Table 2.10: Maximum likelihood estimation results for the CES parameters $\eta$ and $\rho_\ell$ with clustered neighbourhoods of varying sizes. Table 2.5 shows the corresponding baseline elasticity values. Standard errors in parentheses.

Elasticity results under cluster neighbourhoods are very similar to the results generated using the community areas in Table 2.5. In particular, the elasticity between sectors $\eta$ is again slightly greater than 2 and the within-sector elasticities have similar values and ranking orders. This provides supporting evidence that the results presented above are not an artifact of the community area neighbourhood boundaries.

The estimation results suggest that consumer preference for variety is stronger with smaller clusters in the “Drinks and amusement” and “Drinks and music” categories. Insofar as consumers are more averse to travelling long distance between venues on a single night out, this may indicate that consumer preference in these categories arises from bar-hopping in the course of a single night. However, the other two sectors do not display a similar pattern.

### 2.5.2 Separate entry and exit rates

In the model presented above, entrants’ actions are estimated partially based on the action of the pool of entrants and incumbents’ actions are estimated partially based on the action of the pool of incumbents. Accordingly, there is an aspect to the estimation that resembles reflection; for example, in a neighbourhood of many successful incumbents with a low exit rate, I observe successful venues and attribute their success to positive agglomeration.
effects\textsuperscript{21}. This may cause concern that the parameter $\sigma$ is not actually capturing the benefits of other nearby venues but some other factor in venues’ decisions — for example, “animal spirits” among entrants that cause them to enter irrationally based on the rate of each others’ entry. Therefore, as an additional check, I address this by estimating the structural parameter from the entry and exit decision separately.

Specifically, I estimate the potential entrants’ entry decisions using the structural value functions as a response to the nonparametric forms of the exit rates and with a separate likelihood maximization estimate the incumbents’ exit decisions using the structural value functions as a response to the nonparametric forms of the entry rates. That is, I estimate the parameter vector $\theta$ from Equation 2.15 using first-stage nonparametric estimates $\hat{h}_e(s)$ from Equation 2.12 for exit rates but structural predictions (which depend on the parameter vector) for entry rates. Then, I repeat this process with first-stage nonparametric estimates $\hat{h}_e(s)$ for the entry rates and structural predictions for the exit rates. While these estimations provide the second-stage likelihood estimation with fewer observations, it ensures that the structural parameters are estimated from one group of agents’ actions in response to another group’s actions.

Table 2.11 shows the elasticity results under these restricted estimation schemes. As show, estimating the structural parameters by matching only the exit rate gives very similar results to the baseline estimates in Table 2.5. However, matching using only the entry rates gives a very poor model fit and disparate values for the elasticity parameters.

It is worth noting that fitting the model using only the exit rates yields a modest improvement to fit of wait times between transitions as compared to the results presented in Figure 2.8. The correlation between observed and predicted wait times averaged over all demographic and regulatory states is 0.507, compared to 0.479 in the baseline results. Perhaps unsurprisingly, this improvement appears to arise from a closer match between observed and predicted entry rates. Relative to the full model, fitting only the exit rates gives less prediction of rapid exit of incumbent venues.

\textsuperscript{21}Note that due to the structural nature of this model this is not reflection in the strictest sense of the term. However, as a check on the model’s ability to identify the profit function, it is useful to check whether this issue influences the results.
### Table 2.11: Maximum likelihood estimation results for the CES parameters $\eta$ and $\rho_\ell$ under estimation matching only the entry rate and only the exit rate. Table 2.5 shows the corresponding baseline elasticity values. Standard errors in parentheses.

<table>
<thead>
<tr>
<th>Elasticity</th>
<th>Symbol</th>
<th>From entry rate</th>
<th>From exit rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between sectors</td>
<td>$\eta$</td>
<td>6.72 (1.3 × 10^{-9})</td>
<td>2.03 (0.002)</td>
</tr>
<tr>
<td>Amusement only</td>
<td>$\rho_1$</td>
<td>45.81 (4.4 × 10^{-8})</td>
<td>4.79 (0.02)</td>
</tr>
<tr>
<td>Drinks only</td>
<td>$\rho_2$</td>
<td>8.25 (9.6 × 10^{-9})</td>
<td>2.25 (0.002)</td>
</tr>
<tr>
<td>Drinks and amusement</td>
<td>$\rho_3$</td>
<td>6.71 (1.3 × 10^{-9})</td>
<td>3.30 (0.20)</td>
</tr>
<tr>
<td>Drinks and music</td>
<td>$\rho_4$</td>
<td>9.93 (8.5 × 10^{-10})</td>
<td>7.31 (0.36)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>2.5.3 Profit from Starbucks</th>
<th></th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>While the estimation results</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>presented above control for</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>observable characteristics</td>
<td></td>
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<tr>
<td>including demographics, transit</td>
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<td></td>
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<td>access, and the nature of the</td>
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<td>built environment, they may still</td>
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<td>be biased by unobservable</td>
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<td>heterogeneity. For example, if</td>
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<td>some other attribute uncorrelated</td>
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<td>characteristics positively</td>
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<td>impacts venue profits and more</td>
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<td>venues enter in neighbourhoods</td>
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<td>with this attribute, then the</td>
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<td>estimation will erroneously</td>
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<td>attribute this increased</td>
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<td>entry rate to consumer preference</td>
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<td>for variety. One particularly</td>
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<td>salient source of potential</td>
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<td>whether the neighbourhood is a</td>
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<td>pleasant area for consumers – for</td>
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<td>pedestrian movement, appealing-</td>
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<td>looking buildings, a positive</td>
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<td>reputation, or other attributes.</td>
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<td>Researchers in the urban planning</td>
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<td>literature refer to these</td>
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<td>aspects of a commercial</td>
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<td>neighbourhood’s aesthetic quality</td>
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<td>and ease of access as the</td>
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<td>“streetscape”²².</td>
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To investigate the possibility that the estimation results above reflect streetscape quality rather than the presence of many nightlife venues, I re-estimate the model using the venues’ response to the local density of Starbucks rather than the local density of other venues. Insofar as Starbucks locations tend to cluster near areas with high consumer foot traffic, Starbucks outlets seem like a reasonable proxy for unobservable streetscape attributes. The

²² Campo and Ryan (2008) describe the importance of the streetscape for nightlife venues. Darchen (2013b) and Zimmerman (2008) discuss policymakers’ attempts to promote nightlife by upgrades and renovations to the streetscape.
same data set that contains the liquor licenses also contains Starbucks locations, including spatial coordinates and entry and exit dates.

Specifically, I re-estimate the model using a profit function of the following form:

$$\pi_{mli} = A_\ell + B_\ell \zeta_m + C_\ell \zeta_m^2 + D_{dm}$$  \hfill (2.19)

In Equation 2.19, $\zeta_m$ is the number of Starbucks locations in neighbourhood $m$, $d_m$ is the vector of demographic attributes in neighbourhood $m$, and $A_\ell$, $B_\ell$, $C_\ell$, and $D$ are parameters to be estimated. Under this model, venues form their forward-looking expectations based on entry and exit of Starbucks locations, which I estimate nonparameterically. I allow the sunk cost of entry to vary with neighbourhood-level regulation as above. If the profit is constant with respect to the number of Starbucks, this provides supporting evidence that $\rho_\ell$ and $\eta$ are actually measuring consumer preference for variety of venues rather than some other local condition.

Table 2.12 shows the resulting parameter values for the relationship between Starbucks density and profit. As shown, the estimations results indicate no systematic role for Starbucks in the profit function. Conditional on neighbourhood attributes, the signs of the coefficients are neither systematically positive nor negative. These results do not support the hypothesis that the preference for variety implied by the results in Table 2.5 is actually driven by unobservable local-level attributes of local commercial districts.
2.6 Conclusion

Economic literature and urban policymakers have recognized that consumer amenities are an important determinant of migration and quality of life. While consumers appear to value nightlife as a particularly important amenity, it has received less attention in the economic literature, possibly due to a scarcity of detailed data. In this paper, I estimate a dynamic structural model which identifies the profit function and consumer preferences for variety from observed venue entry and exit decisions. I use the estimation results to examine counterfactual scenarios of industry dynamics.

The results of the estimation suggest that consumers place a high value on variety in nightlife venues. In particular, consumers have less of a strong preference for access to variety in venues with music and dance (i.e., nightclubs) while they are very sensitive to variety in venues which serve drinks but do not offer additional amenities (i.e., bars). The preference for variety in the latter category is comparable to the preference for variety in highly-variety specific goods in the international trade literature. The CES parameter values for venues with musical performances are comparable to the results in the literature for preference for variety across restaurants.

The results also indicate that nightlife venues face very high barriers to entry. This limits the available variety of venues and lowers consumer welfare. Initially this would seem to suggest that the optimal policy response would include lower barriers to entry. However, as this study does not account for the negative impacts of nightlife venues, the optimal response is less straightforward. In terms of policy applications, this study does estimate the value to nightlife consumers as well as the impact of new venues on incumbents. In particular, if the new entrant is a nightclub then existing venues experience a relatively small decline in their own profits as the draw of additional customers largely compensates for the increased competition.

These results appear to be fairly robust. Changes to specification do not appear to affect the estimates of consumer preference for variety. As well, as discussed above, the structure of the Chicago nightlife industry and additional estimation results rule out plausible alternate explanations for the observed results.
This study also indicates directions for further research in understanding the valuation and development of consumption amenities in cities. In particular, a similar model of consumer preference for high-variety amenities could be used to investigate other urban consumption amenities with limited data — for example, musical performances or other cultural events. With a more detailed data set, one could infer additional details of consumer preference for variety, particularly in terms of consumers preferences across differing income levels or demographic groups. More broadly, a structural model of this form could be used to provide micro-level foundations for models of network formation where participants can potentially gain from increased connectivity, such as Atalay et al. (2011) or Fershtman and Gandal (2011).

The theoretical and empirical results in this study could be extended by allowing greater flexibility in venue location choices. In the current model, entrants can only choose to enter a specific neighbourhood rather than a specific location within the neighbourhood. This could theoretically be relaxed to allow potential entrants to choose a neighbourhood or even to allow potential entrants to choose any location. As mentioned previously, greater flexibility would massively increase the dimensionality of the state space and this estimation would require a much larger data set. However, this extension would allow for a more comprehensive understanding of the agglomerative forces arising from consumer preferences for variety in the nightlife industry.
3 Land value gradients and the level and growth of housing prices

3.1 Introduction

Housing rents and prices have grown significantly more rapidly in Coastal California, and the Northeastern “Acela Corridor” than elsewhere in the U.S. in recent decades.\(^1\) Table 3.1 presents summary statistics for rent and price growth in and away from these “Coastal” markets. The 25th percentile of coastal rent and price growth exceeds the 75th percentile among other markets.

Economists have put forward several explanations for why prices and rents have grown faster in coastal markets. Physical and regulatory supply constraints are a popular explanation (Green, Malpezzi and Mayo (2005), Saiz (2010), Glaeser, Gyourko and Saks (2005), and many others). Moretti (2013), Diamond (2013a), and others have also observed that productivity and amenity appear to have grown more on the coasts than elsewhere.

This paper considers an additional explanation for price growth on the coasts that is motivated by fundamental results in urban economics and real options theory, but has received relatively little empirical attention. We ask if cities where land values are more concentrated have higher levels and growth of housing rents and prices than elsewhere. As a matter of casual observation, New York, Boston, and D.C. are more strongly monocentric than is typical of “flyover” states. On the California Coast, while cities tend to be polycentric, proximity to and views of the ocean appear to command high premiums. Having a “there there” thus seems to be associated with high and rising real estate prices\(^2\).

\(^1\) One might think of these coastal markets as the Gyourko, Mayer and Sinai (2013) list of “Superstar Cities” purged of noise.

\(^2\) Ironically, Gertrude Stein’s remark about no “there there” was about Oakland, part of the San Francisco Bay Area, where location matters much more than most U.S. markets.
Quantile	Annualized Price Growth	Annualized Rental Growth
Non-Coastal	Coastal	Non-coastal	Coastal
Min	-2.1	.1	.1	.9
25th	-.9	.8	.8	1.4
50th	-.6	1.2	1	1.4
75th	-.1	1.6	1.3	1.5
Max	2.1	2.5	1.8	1.7

Table 3.1: Annualized U.S. Census (nominal) median rent growth (1980-2009/2011) and (log real) Freddie Mac Home Price Index growth (1980-2014): Coastal vs. other metropolitan areas

locations within a metropolitan area vary by the time or money cost of commuting to a central point. Locations are described by their distance from the center, and commuting costs are monotonically increasing with distance. If the gradient of the cost function were zero everywhere, there would be no urban land rents, and the cost of a given home on a given lot size would be the same everywhere inside the metropolitan area, and would grow only with construction or land opportunity costs. If the cost gradient is positive, then as the urban boundary increases, the value of land within the boundary grows. We thus know that from a starting point of homogeneity, introducing heterogeneity of land values across locations increases the sensitivity of price growth to growing demand.

Whether the result that a steeper land rent gradient increases the sensitivity of land prices to demand growth extends past a constant zero gradient is a non-trivial theoretical question. Draft work by Joe Williams suggests the answer is yes, because for a given level of demand and expected demand growth, land value growth options are greater in cities with steep gradients, so less land is developed for a given increase in demand. This result may depend, though, on the elasticity of lot size with respect to land price.

We ask empirically whether cities where land quality is more strongly differentiated have enjoyed increasing rents over time by measuring current median rents, historical rent and price appreciation, and forward-looking appreciation as measured by ratios of rent to price.

A technical innovation in this paper is the introduction of a generalized urban land rent gradient that allows for non-monocentricity. Wheaton (2004) presents and summarizes evidence that the monocentric city model of commuting is a poor approximation for most
cities. Greater Los Angeles and San Francisco stand out as metropolitan areas where the monocentric city model might not describe the land market well.

Standard measures, summarized in McMillen (2003), estimate decay from a single center. To allow for polycentricity, rather than measuring a decay from a single central point, we introduce a measure which takes into account conditions over the entire metropolitan area. Specifically, to measure the extent to which some locations are better than other, we estimate land value gradients averaged across all locations in the metropolitan area. Land values are difficult to observe in most metropolitan areas, so we proxy for land rents in two ways. First, we use a proxy for very high land value: Starbucks locations. Casual observation reveals that Starbucks tends to locate in high-traffic neighborhoods. Unlike some retailers, Starbucks has a small footprint, so there is reason to think that their willingness to pay per square foot of land would fall off more steeply with declining location quality than larger retailers, such as Walmart. Walmart and other “big box” stores are rarely found in prime urban locations. A second proxy for land values comes from apartment rents.

An additional contribution of this paper is to ask whether any of the standard explanations for high housing prices on the coasts have value in explaining home prices inside or away from the coasts. There is reason to suspect not. Several studies, including Mian and Sufi (2009) and Huang and Tang (2012) that the volatility of home prices in the 2000s housing cycle is unconditionally highly correlated with supply constraints. However, Davidoff (2013a), recognizing that supply-constrained cities typically feature attractive environments (such as mountains and oceans, the primitive of the standard Saiz (2010) measure of constraints) and productive workers, finds that within states, or conditional on historical measures of demand growth, supply constraints are not associated with price volatility. Davidoff (2015) shows that a coastal indicator swamps many demand measures in explaining historical price growth. An important question is whether urban economists (ourselves included) have explained why the coasts have witnessed more price growth and volatility, or instead have unsuccessfully sought to deduce the drivers of price growth from the performance of set of markets that differ from other U.S. markets in ways that are hard to characterize.
3.2 Theoretical model

We define a city-level measure of the spatial rate of change of local land value. To discuss this measure, it will be helpful to define some notation. For a given city in the data, we observe a collection of pairs \((x_i, y_i)\) for \(i \in 1, 2, \ldots, N\) where \(x_i\) is a spatial position and \(y_i\) is a corresponding rent observation. The density of observations corresponds to the realization of some underlying probably distribution \(f(x)\) for rent observations at location \(i\). The value of \(y_i\) corresponds to the realization of some valuation function \(y_i = r(x_i) + \varepsilon_i\) where \(r(x) = \mathbb{E}[y | x]\) is the expected rent conditional on location. Our measure focuses on the rate of change in this expected rent function \(r\).

Specifically, we estimate the average magnitude of the density-weighted gradient of rent. The gradient of \(r\) is defined by the vector \(\frac{\partial r}{\partial x}\). Its magnitude corresponds to the rate of increase in \(r\) along the direction of steepest ascent; a larger magnitude for the vector \(\frac{\partial r}{\partial x}\) corresponds to a situation where rents change more rapidly with position.

Powell, Stock and Stoker (1989) and Powell and Stoker (1996) describe estimators for the average density-weighted gradient \(\mathbb{E}[f(x) \frac{\partial r}{\partial x}]\). The argument to the expectation here is the rate of change in \(r\) with respect to position, weighted by the density of observations. This vector-valued expectation describes the average rate of change of rent (with respect to marginal changes in position northward and eastward) across the entire city. This measure is unsuitable for our purposes as averaging the vector of spatial derivatives over the extent of a city can give an average vector for which the magnitude is difficult to interpret. For example, a constant-density city where rents decrease smoothly and symmetrically with distance from the city centre would have an average density-weighted gradient of zero, as each observation would be precisely cancelled out in the average by an observation on the opposite side of downtown.

Instead, we consider the magnitude of the average density-weighted gradient of rent, defined as \(\bar{g} = \mathbb{E}[f(x) \frac{\partial r}{\partial x}]\). This scalar-valued measure describes the average absolute rate of change in rents with respect to position. To estimate \(\bar{g}\), we form an estimate \(\hat{f}(x)\) of the density of observations \(f(x)\) using a kernel density estimator and an estimate \(\hat{\frac{\partial r}{\partial x}}\) of the gradient magnitude \(\frac{\partial r}{\partial x}\) from a local cubic regression of rent as a function of position.
Then, we take the sample analogue of $\tilde{g}$ to obtain an estimate $\hat{g}$:

$$\hat{g} = \frac{1}{N} \sum_{i=1}^{N} \hat{f}(x_i) \left| \frac{\partial \hat{r}(x_i)}{\partial x} \right|$$  \hspace{1cm} (3.1)

As $\hat{f}(x)$ consistently estimates $f(x)$ and $\left| \frac{\partial \hat{r}(x_i)}{\partial x} \right|$ consistently estimates $\left| \frac{\partial r}{\partial x} \right|$, Equation 3.1 yields a consistent estimate of $\tilde{g}$.

The kernel density estimate of $f(x)$ requires a bandwidth parameter to determine the spatial scale of smoothing. While the optimal bandwidth for $\tilde{g}$ is not well studied, Powell and Stoker (1996) provide an algorithm for estimating the optimal bandwidth for $\mathbb{E} \left[ f(x) \frac{\partial r}{\partial x} \right]$. We use this procedure to estimate a bandwidth for each city in our sample. While the bandwidth described by Powell and Stoker (1996) minimizes the mean squared error for the vector $f(x) \frac{\partial r}{\partial x}$ over the extent of the city, this is likely a close approximation to the bandwidth which minimizes the mean squared error of its magnitude $f(x) \left| \frac{\partial r}{\partial x} \right|$.

We estimate $\tilde{g}$ for one-bedroom apartment rent and for the local density of Starbucks outlets. For the rent gradient, we can use observed rents directly as $y_i$. For the Starbucks gradient, we use the method suggested in Ruppert (1997) to form a consistent binned estimate of the density of Starbucks locations (with bins over the extent of the metropolitan statistical area) and use this estimate as $y_i$.

### 3.3 Data sources

To calculate the gradient measure $\tilde{g}$ as described above, we collect data on local rent conditions at a fine level of spatial disaggregation. To test the role of these gradient measures in the price response to a demand shock, we collect data on price movements, demand shocks, and additional controls related to supply elasticity and housing markets.

#### 3.3.1 Location-specific value

For precise estimates of the gradient measure described above, we require data on locational values at a spatially fine level within metropolitan areas. We use two measures: the location of Starbucks coffee shops and the rent for one-bedroom apartments listed on Craigslist.
We obtain a list of Starbucks locations in the United States from the Starbucks website. Starbucks locations have a steep bid-rent curve and tend to cluster disproportionately in affluent areas with high levels of commercial activity (Meltzer and Schuetz, 2012; Davidoff, 2013). These attributes make Starbucks a feasible proxy for the presence of higher-rent retail districts.

Figure 3.1 shows the distribution of Starbucks locations in four representative urban areas. As shown, Starbucks locations are very heavily clustered downtown within New York City and San Francisco and highly dispersed around Los Angeles and Phoenix. We use the location of Starbucks to calculate a gradient measure as discussed above. The gradient scores, in parentheses, are consistent with visual inspection.

We gather rent data at a fine level of spatial disaggregation by scraping Craigslist rental apartment listings. In addition to the asking rent, the number of bedrooms, and the square footage, these listings indicate the spatial coordinates of the housing for rent to a high degree of geographical precision. Table 3.2 shows summary statistics for the Craigslist rent data. Throughout, the unit of observation is the median value for a metropolitan statistical area. (We aggregate rent data to the MSA level to match the price data described below.) Information on square footage is somewhat less complete than information on rent; 30% of ads include a rent but not a square footage.

To calculate a locationality measure from the rent data, we use only the rent for one-bedroom units. Insofar as one-bedroom units are likely to be comparable in structural

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<th>Mean</th>
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<tr>
<td>1 bedroom</td>
<td></td>
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<tr>
<td>Rent ($)</td>
<td>744</td>
<td>372</td>
<td>227</td>
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<tr>
<td>Square footage</td>
<td>712</td>
<td>129</td>
<td>198</td>
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<tr>
<td>2 bedroom</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Rent ($)</td>
<td>945</td>
<td>616</td>
<td>244</td>
</tr>
<tr>
<td>Square footage</td>
<td>1024</td>
<td>177</td>
<td>217</td>
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<tr>
<td>3 bedroom</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rent ($)</td>
<td>1145</td>
<td>556</td>
<td>259</td>
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<tr>
<td>Square footage</td>
<td>1528</td>
<td>747</td>
<td>240</td>
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<tr>
<td>4 bedroom</td>
<td></td>
<td></td>
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<tr>
<td>Rent ($)</td>
<td>1634</td>
<td>695</td>
<td>182</td>
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<tr>
<td>Square footage</td>
<td>2045</td>
<td>487</td>
<td>167</td>
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Table 3.2: Summary statistics for the Craigslist rent location data. Throughout, the unit of observation is the MSA.
attributes, one-bedroom rent reflects the varying value of underlying land. Therefore, the rent of a one-bedroom apartment is a reasonable measure of the spatial variation in the value of locations within a city.

Figure 3.2 shows the spatial distribution of one-bedroom rental units across four sample
Figure 3.2: Spatial distribution of one-bedroom apartments in four sample cities, together with monthly rent.

markets, together with prices. As shown, the Craigslist rental data provides spatially dense coverage of residential areas.

3.3.2 Price data

As we cannot directly observe the present market price of the housing units in the sample, we use housing price information from Zillow. Zillow is a proprietary service which compiles housing data for the United States. Previous economic studies including Hubbard and
Mayer (2009), Mian and Sufi (2011), and Huang and Tang (2012) have used Zillow. The authors of these studies note its close correlation with other housing price indices. This data set includes a housing price for each zipcode for 1, 2, 3, and 4-bedroom apartments. To match the Craigslist rent data discussed above, we use the Zillow values for March 2014. Table 3.3 shows summary statistics for the Zillow rent data. Throughout, the unit of observation is the metropolitan statistical area.

We use the ratio of housing prices to housing rent as a measure of the price response to a demand shock, or alternatively the market expectation of future price growth conditional on demand. A model of housing as an investment asset provides a rationale for this measure. Let $P$ be the current price of a house, $R$ be the rent, and $P'$ be the expected future price of the house. Then, the return $i$ on owning the house is given by $i = \frac{R}{P} + \frac{P'}{P}$ — that is, the return is equal to the dividend plus the capital appreciation. If the equilibrium rate of return $i$ is constant across cities (e.g., if it is equal to the economywide rate of return on investment assets) then differences in the price-rent ratio $\frac{R}{P}$ reflect differences in the price appreciation $\frac{P'}{P}$. Studies have used the price-rent ratio for housing to assess how far the price of housing has diverged from “fundamental” levels and to indicate the presence of housing market bubbles (Davis, Lehnert and Martin, 2008; Campbell et al., 2009; Duca, Muellbauer and Murphy, 2011). In a retrospective review of the drastic house-price cycle of the 2000s, Gerardi, Foote and Willen (2010) point to the divergent price-rent ratio as evidence for a potential housing price bubble.

As the Zillow data set includes historical prices, it is possible to directly compare ob-

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<th>Mean</th>
<th>Std dev</th>
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<tr>
<td>1 bedroom</td>
<td>Price ($1000)</td>
<td>136</td>
<td>95</td>
</tr>
<tr>
<td></td>
<td>Price-rent ratio</td>
<td>140</td>
<td>86</td>
</tr>
<tr>
<td>2 bedroom</td>
<td>Price ($1000)</td>
<td>141</td>
<td>94</td>
</tr>
<tr>
<td></td>
<td>Price-rent ratio</td>
<td>141</td>
<td>41</td>
</tr>
<tr>
<td>3 bedroom</td>
<td>Price ($1000)</td>
<td>186</td>
<td>113</td>
</tr>
<tr>
<td></td>
<td>Price-rent ratio</td>
<td>159</td>
<td>75</td>
</tr>
<tr>
<td>4 bedroom</td>
<td>Price ($1000)</td>
<td>261</td>
<td>140</td>
</tr>
<tr>
<td></td>
<td>Price-rent ratio</td>
<td>181</td>
<td>127</td>
</tr>
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Table 3.3: Summary statistics for the Zillow price data and the rent-price ratio from the Zillow price and Craigslist rent data. Throughout, the unit of observation is the MSA.
served price-rent ratios to changes in housing prices. At each unit size, the median price-rent ratio at the zipcode level in our data set and the year-over-year change in zipcode-level housing prices are positively correlated to a high degree of statistical significance.

### 3.3.3 Additional controls

In addition to the gradient measures described above, we control for existing measures of supply elasticity from the literature, growth in housing demand, and property taxes. Specifically, we control for supply elasticity measures from Saiz (2010), which measures the share of land near the centre of the metro area available for building housing and from Gyourko, Saiz and Summers (2008), which measures the regulatory stringency applied to the construction of new housing.

To construct a measure of growth in housing demand, we follow Bartik (1991) and Blanchard and Katz (1992) to define Bartik shocks, which interact the variation cities in industrial composition with the variation between industries in performance at the national level. Specifically, we calculate the Bartik shock for metro area $m$ between years $t_1$ and $t_2$ as follows:

$$B_m = \sum_{ind} \left( N_{ind}^{m,t_2} - N_{ind}^{m,t_1} \right) \frac{N_{ind}^{m,t_1}}{\sum_{ind'} N_{ind'}^{m,t_1}}$$  \hspace{1cm} (3.2)

In Equation 3.2 the superscript $ind$ indexes industries and $N_{ind}^{m,t}$ is number of workers in industry $ind$ in MSA $m$ at time $t$. The notation $-m$ denotes the wage for all metro areas other than metro area $m$. As defined in Equation 3.2, the Bartik shock is positive in metro areas with improving labour market outcomes and negative in metro areas with worsening labour market outcomes.

We calculate values for the Bartik shocks using data from 1980 and 2010 Census data. We divide industries at the two-digit level. Following Guerrieri, Hartley and Hurst (2013) and others, we restrict the labour force sample to full-time workers (at least 48 weeks of work in the past year with at least thirty hours of work in the typical week) aged between 25 and 55.

Unfortunately, no data set contains property tax rates for all municipalities. However, Minnesota Taxpayers Association (2011) reports property tax levels in all fifty states and
Table 3.4 shows summary statistics for these additional variables. Throughout, the unit of observation is the metropolitan area.

### 3.4 Empirical results

Figure 3.3 compares the Starbucks and rent gradient measures. As shown, among large metropolitan areas, Chicago, Boston, San Francisco, and New York have high particularly high gradients. These two gradient measures measures are highly correlated with each other; as well, they are highly correlated with the measures of supply inelasticity from the literature. Table 3.5 shows the correlations between these measures. These high correlations are unsurprising; all of these measures capture the high-amenity, high-regulation, predominantly high-income “superstar” cities highlighted in Gyourko, Mayer and Sinai (2013).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std dev</th>
<th>N</th>
</tr>
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<tbody>
<tr>
<td>Bartik shock</td>
<td>0.617</td>
<td>0.178</td>
<td>117</td>
</tr>
<tr>
<td>Unusable land (%)</td>
<td>25.1</td>
<td>20.8</td>
<td>82</td>
</tr>
<tr>
<td>WRLURI</td>
<td>0.115</td>
<td>0.691</td>
<td>82</td>
</tr>
<tr>
<td>Population (million)</td>
<td>1.74</td>
<td>2.49</td>
<td>117</td>
</tr>
<tr>
<td>Starbucks count</td>
<td>135</td>
<td>157</td>
<td>73</td>
</tr>
<tr>
<td>Property tax (%)</td>
<td>1.76</td>
<td>0.86</td>
<td>111</td>
</tr>
<tr>
<td>Coastal status</td>
<td>0.154</td>
<td>0.362</td>
<td>117</td>
</tr>
<tr>
<td>Graduate degree (%)</td>
<td>5.12</td>
<td>1.98</td>
<td>116</td>
</tr>
<tr>
<td>Democratic lean</td>
<td>-0.338</td>
<td>0.323</td>
<td>116</td>
</tr>
</tbody>
</table>

Table 3.4: Summary statistics for additional control variables.

the District of Columbia as well as separate rates for New York City and Chicago (which differ substantially from property tax levels in other parts of their respective states). We use the rates reported for urban apartment property taxes in this report.

To investigate the relationship of these measures with the response of housing prices to a demand shock, we regress the rent, the price-rent ratio, and the long-term housing price growth on the gradient measures, the Bartik shock, and other measures of supply elasticity. Each observation is a MSA-bedroom count pair. We use this factor to weight regressions that include the Starbucks gradient or rent gradient. We control for heterogeneity within
Figure 3.3: Comparison of rent gradient and Starbucks density gradient for metropolitan areas in the sample. Metropolitan areas with a population greater than three million are labelled by their principal cities.

<table>
<thead>
<tr>
<th></th>
<th>Rent gradient</th>
<th>Unusable land</th>
<th>WRLURI</th>
<th>Coastal</th>
<th>Democratic lean</th>
<th>Grad degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starbucks gradient</td>
<td>0.190</td>
<td>0.145</td>
<td>0.207</td>
<td>0.247</td>
<td>0.426</td>
<td>0.395</td>
</tr>
<tr>
<td>Rent gradient</td>
<td>0.297</td>
<td>0.155</td>
<td>0.274</td>
<td>-0.115</td>
<td>0.052</td>
<td></td>
</tr>
<tr>
<td>Unusable land</td>
<td>0.37</td>
<td>0.38</td>
<td>0.38</td>
<td>0.42</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WRLURI</td>
<td>0.43</td>
<td>0.48</td>
<td>0.47</td>
<td>0.49</td>
<td>0.71</td>
<td></td>
</tr>
<tr>
<td>Coastal</td>
<td>0.43</td>
<td>0.48</td>
<td>0.49</td>
<td>0.71</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Democratic lean</td>
<td>0.47</td>
<td>0.49</td>
<td>0.71</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.5: Correlations between supply inelasticity factors. Throughout, the unit of observation is the metropolitan area.

each bedroom count by including a separate control for square footage for each bedroom count and control for heterogeneity in the user cost of housing by controlling for property taxes. Throughout, we control for potential scale effects by controlling for the population of the MSA and the number of Starbucks locations. All extensive variables are in logarithms while index variables are untransformed.
Table 3.6: Regression results for the current rent without the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Intercept</th>
<th>Bartik shock</th>
<th>WRLURI</th>
<th>Unusable land</th>
<th>Starbucks gradient</th>
<th>Rent gradient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>−9.100*</td>
<td>−7.862*</td>
<td>−4.731</td>
<td>−4.739</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.910)</td>
<td>(4.610)</td>
<td>(4.904)</td>
<td>(4.802)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bartik shock</td>
<td>0.084</td>
<td>0.130</td>
<td>0.075</td>
<td>0.111</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.168)</td>
<td>(0.180)</td>
<td>(0.167)</td>
<td>(0.178)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WRLURI</td>
<td>0.220***</td>
<td>0.204***</td>
<td>0.215***</td>
<td>0.208***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td>(0.069)</td>
<td>(0.069)</td>
<td>(0.072)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unusable land</td>
<td>0.094**</td>
<td>0.078*</td>
<td>0.067*</td>
<td>0.065</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.040)</td>
<td>(0.040)</td>
<td>(0.041)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Starbucks gradient</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.064***</td>
<td>0.053**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.021)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Rent gradient</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.101**</td>
<td>0.062</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.047)</td>
</tr>
<tr>
<td>Observations</td>
<td>243</td>
<td>243</td>
<td>236</td>
<td>236</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.626</td>
<td>0.642</td>
<td>0.635</td>
<td>0.644</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.6 shows results for regressions of median housing rent on the Bartik shock, unusable land, and regulatory stringency. The supply elasticity and gradient proxies all have significantly positive relationships with rent unconditionally. The supply and gradient proxies, not surprisingly, reduce each others’ magnitude in combination. As shown in Table 3.7, when the Coastal indicator is included, its coefficient is highly statistically significant. Again, the Coastal indicator has substantial explanatory power even conditional on all other controls.

Table 3.8 show regression results for the price-rent ratio on the Bartik shock, the WRLURI and the share of unbuildable land, and the Starbucks and rent gradients. As shown, the covariates that measure supply constraints have a positive relationship with the price-rent ratio. Given that the price-rent ratio measures the expected price increase, it seems reasonable that a measure of a positive demand shock and measures of supply inelasticity would show this positive relationship. However, only the Starbucks gradient is consistently highly statistically significant. In particular, the coefficient on the Starbucks gradient is consistent across regressions, including a specification which includes both the Starbucks
<table>
<thead>
<tr>
<th></th>
<th>Intercept</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>11.615***</td>
<td>10.483**</td>
<td>6.275</td>
<td>6.263</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4.413)</td>
<td>(4.259)</td>
<td>(3.910)</td>
<td>(3.897)</td>
</tr>
<tr>
<td>Bartik shock</td>
<td>0.053</td>
<td>0.087</td>
<td>0.037</td>
<td>0.039</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.147)</td>
<td>(0.158)</td>
<td>(0.136)</td>
<td>(0.141)</td>
<td></td>
</tr>
<tr>
<td>WRLURI</td>
<td>0.119</td>
<td>0.121</td>
<td>0.083</td>
<td>0.084</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.081)</td>
<td>(0.096)</td>
<td>(0.098)</td>
<td></td>
</tr>
<tr>
<td>Unusable land</td>
<td>0.076**</td>
<td>0.068*</td>
<td>0.030</td>
<td>0.031</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.038)</td>
<td>(0.036)</td>
<td>(0.036)</td>
<td></td>
</tr>
<tr>
<td>Starbucks gradient</td>
<td>0.043**</td>
<td></td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td></td>
<td>(0.027)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rent gradient</td>
<td></td>
<td></td>
<td>0.153***</td>
<td>0.151**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.051)</td>
<td>(0.059)</td>
<td></td>
</tr>
<tr>
<td>Coastal</td>
<td>0.318***</td>
<td>0.279***</td>
<td>0.401***</td>
<td>0.398***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td>(0.073)</td>
<td>(0.084)</td>
<td>(0.099)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>243</td>
<td>243</td>
<td>236</td>
<td>236</td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.661</td>
<td>0.667</td>
<td>0.687</td>
<td>0.686</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.7: Regression results for current rent with the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

As shown in Table 3.9, conditional on the Coastal indicator, neither the Starbucks gradient nor the supply constraint measures are not significant.

Table 3.10 presents regressions similar to those in Tables 3.8 and 3.6, with the dependent variable reflecting realized past price and rent growth, rather than the current level of rent or implied market rent growth expectations. In Table 3.10, the dependent variable is real Federal Housing Finance Agency Home Price Index growth between October, 1980 and October, 2014, at the metropolitan level. The supply constraints and the Starbucks gradient are statistically significant predictors here. Table 3.11 incorporates the Coastal indicator. As above, the Coastal indicator is highly statistically significant and the statistical significance of other coefficients is generally reduced.
<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>5.764</td>
<td>6.733</td>
<td>5.816</td>
<td>5.741</td>
</tr>
<tr>
<td></td>
<td>(5.556)</td>
<td>(5.548)</td>
<td>(5.655)</td>
<td>(5.532)</td>
</tr>
<tr>
<td>Bartik shock</td>
<td>0.036</td>
<td>0.063</td>
<td>0.037</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td>(0.145)</td>
<td>(0.158)</td>
<td>(0.147)</td>
<td>(0.154)</td>
</tr>
<tr>
<td>WRLURI</td>
<td>0.069</td>
<td>0.061</td>
<td>0.068</td>
<td>0.063</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.051)</td>
<td>(0.052)</td>
<td>(0.051)</td>
</tr>
<tr>
<td>Unusable land</td>
<td>0.040</td>
<td>0.032</td>
<td>0.040</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.032)</td>
<td>(0.034)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Starbucks gradient</td>
<td>0.034**</td>
<td></td>
<td>0.040**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td></td>
<td>(0.016)</td>
<td></td>
</tr>
<tr>
<td>Rent gradient</td>
<td>0.000</td>
<td></td>
<td>−0.029</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td></td>
<td>(0.038)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>218</td>
<td>218</td>
<td>214</td>
<td>214</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.437</td>
<td>0.451</td>
<td>0.434</td>
<td>0.450</td>
</tr>
</tbody>
</table>

Table 3.8: Regression results for the price-rent ratio without the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

### 3.5 Conclusion

Consistent with intuition and an elementary monocentric city model, land rents are on average greater in markets where location matters. Some of the relationship between housing costs and conventional measures of supply elasticity appear to be attributable to land rent gradients, but it is difficult to draw conclusions about causality given high correlations among multiple measures of constraints on growth and demand factors such as Bartik shocks, average education, and environmental amenity. Notably, across specifications, a number of attributes shared by coastal metropolitan areas fail to explain away the high prices in those markets.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate 1</th>
<th>Estimate 2</th>
<th>Estimate 3</th>
<th>Estimate 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.098</td>
<td>1.215</td>
<td>3.052</td>
<td>2.946</td>
</tr>
<tr>
<td></td>
<td>(3.425)</td>
<td>(3.560)</td>
<td>(3.529)</td>
<td>(3.481)</td>
</tr>
<tr>
<td>Bartik shock</td>
<td>−0.013</td>
<td>−0.010</td>
<td>−0.013</td>
<td>−0.025</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.108)</td>
<td>(0.107)</td>
<td>(0.106)</td>
</tr>
<tr>
<td>WRLURI</td>
<td>−0.050</td>
<td>−0.050</td>
<td>−0.062</td>
<td>−0.067</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.044)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Unusable land</td>
<td>0.029</td>
<td>0.029</td>
<td>0.015</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.025)</td>
<td>(0.027)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Starbucks gradient</td>
<td>0.003</td>
<td></td>
<td>−0.014</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td></td>
<td>(0.021)</td>
<td></td>
</tr>
<tr>
<td>Rent gradient</td>
<td></td>
<td></td>
<td>0.052**</td>
<td>0.064*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.025)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Coastal</td>
<td>0.376***</td>
<td>0.374***</td>
<td>0.402***</td>
<td>0.421***</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.052)</td>
<td>(0.048)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Observations</td>
<td>218</td>
<td>218</td>
<td>214</td>
<td>214</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.604</td>
<td>0.602</td>
<td>0.612</td>
<td>0.612</td>
</tr>
</tbody>
</table>

Table 3.9: Regression results for the price-rent ratio with the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>5.213</td>
<td>7.457</td>
<td>7.127</td>
<td>5.288</td>
</tr>
<tr>
<td></td>
<td>(5.161)</td>
<td>(5.086)</td>
<td>(8.532)</td>
<td>(8.088)</td>
</tr>
<tr>
<td>Bartik shock</td>
<td>−0.055</td>
<td>−0.002</td>
<td>−0.064</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.236)</td>
<td>(0.235)</td>
<td>(0.230)</td>
<td>(0.228)</td>
</tr>
<tr>
<td>WRLURI</td>
<td>0.350***</td>
<td>0.326***</td>
<td>0.348***</td>
<td>0.329***</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.074)</td>
<td>(0.084)</td>
<td>(0.074)</td>
</tr>
<tr>
<td>Unusable land</td>
<td>0.135***</td>
<td>0.115**</td>
<td>0.127**</td>
<td>0.124**</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.045)</td>
<td>(0.056)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Starbucks gradient</td>
<td>0.077**</td>
<td></td>
<td>0.085***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td></td>
<td>(0.032)</td>
<td></td>
</tr>
<tr>
<td>Rent gradient</td>
<td></td>
<td></td>
<td>0.030</td>
<td>−0.034</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.085)</td>
<td>(0.086)</td>
</tr>
<tr>
<td>Observations</td>
<td>60</td>
<td>60</td>
<td>59</td>
<td>59</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.587</td>
<td>0.616</td>
<td>0.568</td>
<td>0.599</td>
</tr>
</tbody>
</table>

Table 3.10: Regression results for the long-term price growth without the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
<table>
<thead>
<tr>
<th>Term</th>
<th>Estimate</th>
<th>SE</th>
<th>Estimate</th>
<th>SE</th>
<th>Estimate</th>
<th>SE</th>
<th>Estimate</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-6.544**</td>
<td>(3.088)</td>
<td>-5.693</td>
<td>(3.820)</td>
<td>-0.776</td>
<td>(5.262)</td>
<td>-0.722</td>
<td>(5.151)</td>
</tr>
<tr>
<td>Bartik shock</td>
<td>-0.035</td>
<td>(0.166)</td>
<td>-0.024</td>
<td>(0.174)</td>
<td>-0.064</td>
<td>(0.154)</td>
<td>-0.072</td>
<td>(0.163)</td>
</tr>
<tr>
<td>WRLURI</td>
<td>0.117*</td>
<td>(0.068)</td>
<td>0.118*</td>
<td>(0.067)</td>
<td>0.099</td>
<td>(0.072)</td>
<td>0.096</td>
<td>(0.075)</td>
</tr>
<tr>
<td>Unusable land</td>
<td>0.097***</td>
<td>(0.035)</td>
<td>0.093**</td>
<td>(0.036)</td>
<td>0.067*</td>
<td>(0.041)</td>
<td>0.067</td>
<td>(0.041)</td>
</tr>
<tr>
<td>Starbucks gradient</td>
<td>0.017</td>
<td>(0.026)</td>
<td></td>
<td></td>
<td>-0.010</td>
<td>(0.031)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rent gradient</td>
<td></td>
<td></td>
<td>0.097*</td>
<td>(0.058)</td>
<td>0.105*</td>
<td>(0.061)</td>
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<td>0.665***</td>
<td>(0.085)</td>
<td>0.715***</td>
<td>(0.070)</td>
<td>0.729***</td>
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Table 3.11: Regression results for the long-term price growth with the Coastal indicator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
4 A control function approach to the correlated components of Bartik shocks

4.1 Introduction

A Bartik shock is an instrument for local aggregate demand. It is intended as a source of exogenous variation in situations where aggregate demand may be simultaneously determined with the outcome variable of interest. For example, Paciorek (2013) uses Bartik shocks as an instrument for demand in a study of cross-sectional differences in housing price dynamics, Partridge et al. (2012) uses Bartik shocks as an instrument in a study of within-US migration, and Luttmer (2005) uses Bartik shocks as an instrument in a study of neighbours’ economic performance and subjective well-being. Bartik (1991) and Blanchard and Katz (1992) initially popularized this instrumentation strategy. As documented in Baum-Snow and Ferreira (2014), Bartik shocks are now widely used in urban economics.

Bartik shocks are typically useful when regressing some city-level outcome variable of interest on demand growth. For example, consider estimating a housing supply curve by regressing price growth $P_i$ on employment growth $Y_i$:

$$P_i = \alpha + \beta Y_i + e_i$$  \hspace{1cm} (4.1)

Estimating this equation via OLS will not necessarily yield consistent estimates, as in general employment growth $Y_i$ is not exogenous to price growth — that is, $\mathbb{E}[Y_i, e_i] \neq 0$. As discussed in detail below, this endogeneity could arise through local demand shocks from city-specific amenities, scarcity of land for housing and other economic activity, or local government decisions on land use regulations or infrastructure. To address this potential endogeneity, it would be helpful to find an instrument $B_i$ that predicts labour demand $Y_i$ (i.e., $\mathbb{E}[B_i, Y_i] \neq 0$) but which is excluded from the second-stage regression (i.e., $\mathbb{E}[B_i, e_i] = 0$).
The Bartik shock is designed to provide such an instrument. It is defined by interacting national-level industry trends with local industrial composition. Specifically, if $y_{ij}$ is the growth in employment in city $i$ in industry $j$, $\kappa_{ij}$ is the share of the population of city $i$ in industry $j$, and $I$ is the number of cities, then the Bartik shock $B_i$ for city $i$ is defined as follows:

$$B_i = \sum_j \kappa_{ij} \left( \frac{1}{I-1} \sum_{i' \neq i} y_{i'j} \right)$$  

(4.2)

Insofar as employment growth in city $i$ in industry $j$ is correlated with employment growth in city $i' \neq i$ in industry $j$, $B_i$ will be correlated with aggregate employment growth in city $i$. The utility of the Bartik shock as an instrument arises from the insight that employment in all cities in all industries is affected by national industry-level trends, but the trend for a given industry has more impact in a city where the industry employs a greater share of the population. For example, the Bartik shock calculation for Cleveland would place a higher weight on the nationwide performance of manufacturing in the rest of the country and a lower weight on the nationwide performance of tourism than the Bartik shock calculation for Las Vegas.

To be an effective instrument, the Bartik shock must have strong predictive power and it must be exogenous to the outcome variable of interest. Studies including Duranton and Turner (2011), Luttmer (2005), and Aizer (2010) have tested the predictive power of the Bartik shock instrument — that is, the ability of the Bartik shock to predict changes in employment. They report that the instrument has strong first-stage predictive power.

The exogeneity of the Bartik shock is more complicated to interpret. In situations where the outcome variable of interest is likely unrelated to the composition of the local labour force (as in, e.g., Aizer (2010)), then it is probably reasonable to treat the Bartik shock as an exogenous shift in local labour demand. However, if the outcome variable of interest is likely correlated with the city’s industrial composition, then Bartik shocks are less unambiguously exogenous, as high-Bartik shock and low-Bartik shock cities may be systematically different in ways that impact the outcome variable. For example, this correlation with industrial composition could arise via productivity spillovers between industries (as discussed in, e.g.,
Moretti (2004) and Beaudry, Green and Sand (2012) or amenities correlated with industrial composition (as discussed in, e.g., Rappaport (2008) and Diamond (2013b)). Davidoff (2015) finds that the Bartik shock for a given city is highly correlated with city-level attributes including scarcity of buildable land, stringency of land use regulation, and the initial share of immigrants in the population.

Researchers using instrumentation strategies based on Bartik shocks are aware of this potential complication. In their discussion of using the Bartik shock as an instrument, Baum-Snow and Ferreira (2014) express the concern as follows:

> [I]t may be the case that manufacturing intensive cities have declined not only because the demand for skill has declined more in these locations, but also because they have deteriorated more in relative amenity values with the increasing blight and decay generated by obsolete manufacturing facilities.

As discussed in further detail below, many papers that use the Bartik shock as a source of identifying variation assume its exogeneity in situations where this assumption seems very strong. However, some studies do explicitly test whether relevant sources of endogeneity are possible. Beaudry, Green and Sand (2012) and Beaudry, Green and Sand (2014) address the possibility that workers migrate away from cities where a high-paying industry is leaving regardless of the industry in which they are currently working as the workers perceive the probability of acquiring a high-paying job to be decreasing. They test for this scenario using a Heckman selection-type procedure based on Dahl (2002) and for their application they find no significant effect.

In this study, I introduce a novel control function approach to accounting for this additional potential endogeneity. This approach isolates the city-specific component of labour market performance and then uses it to account for the correlation of potentially endogenous residual terms with industrial composition. It may be used separately or together with the Bartik shock instrument.

The derivation of the control function approach requires an additional identifying assumption on the correlations between error terms. Due to the additional assumption, the approach introduced here represents a potential improvement over the Bartik shock instru-
ment primarily in situations where the potentially endogenous components of the residual are correlated with the city-specific component of employment growth. For example, if the residual term is potentially endogenous due to productivity spillovers from dominant industries, and productivity spillovers are strongly correlated with the city-specific component of employment growth, then the assumption required to motivate the control function is likely justifiable. As with any identifying assumption, it cannot be tested. Therefore, any empirical application of the control function approach should likely be accompanied by a theoretical argument that rationalizes this identifying assumption.

To demonstrate the application of this new technique, I estimate a housing supply function with and without the Bartik shock as an instrument and with and without the control function adjustment. For this particular empirical application, the control function adjustment has a modest but statistically significant impact on coefficient estimates. I discuss the relative performance of the Bartik instrument and control function estimators in the context of the two techniques’ underlying identifying assumptions.

The remainder of this study is organized as follows. In the next section, I discuss how effects arising from industrial composition can interfere with the exogeneity assumptions required for the Bartik shock instrument and propose a control function approach to address this issue. Then, I estimate this model using United States labour force and housing market data to examine the impact of the control function adjustment in an empirical context.

4.2 Theoretical model

In this section, I discuss the potential endogeneity of the Bartik shock instrument. I describe the theoretical model that underlies the instrument, identify the potential endogeneity, and discuss how this endogeneity relates to common uses of Bartik shock instruments in the literature. Then, I introduce a control function approach that may mitigate this endogeneity in some situations.

Before proceeding, it will be useful to define some notation. Consider a population of workers in cities \( i \in 1, 2, \ldots, I \) and industries \( j \in 1, 2, \ldots, J \). I consider a situation with fixed \( J \) and asymptotically large \( I \) — for example, \( J \) is the set of one-digit industrial
classifications and $I$ is the set of all metropolitan areas in the United States. Let $Y_i$ denote employment growth in city $i$ and let $y_{ij}$ denote employment growth in city $i$ in industry $j$. (Throughout, I consider employment growth over a single time period — for example, a single decadal Census.) Let $\kappa_{ij}$ be the share of the population in city $i$ employed in industry $j$ at the beginning of the time period. Then, $Y_i$ and $y_{ij}$ are related by $Y_i = \sum_j \kappa_{ij}y_{ij}$. For notational convenience, define $\kappa_i$ to be the vector composed of $\kappa_{ij}$ for $j \in 1, 2, \ldots, J$.

For city $i$ and industry $j$, the employment growth $y_{ij}$ may be decomposed without loss of generality as the sum of a city-specific term $u_i$, an industry-specific term $v_j$, and an uncorrelated residual term $\varepsilon_{ij}$:

$$y_{ij} = u_i + v_j + \varepsilon_{ij} \quad (4.3)$$

The use of Bartik shocks as an instrument is motivated by the supposition that the industry trends for broadly-defined industries $j$ are determined by exogenous macro-level circumstances. Accordingly, I consider a framework where the $v_j$ terms in Equation 4.3 are predetermined while the city-specific $u_i$ terms, the idiosyncratic city-industry $\varepsilon_{ij}$ terms and the industrial composition $\kappa_i$ terms are jointly drawn from some unknown distribution $G(u, \varepsilon, \kappa)$ independently for each city $i \in I$. Also without loss of generality, assume the data is suitably de-meaned such that $\mathbb{E}[u_i] = \mathbb{E}[\varepsilon_{ij}] = 0$.

The Bartik shock is intended to control for the endogeneity caused by correlation between the city-specific component of employment growth $u_i$ and the outcome variable of interest. For example, consider estimating a housing supply curve by regressing house price growth $P_i$ on employment growth $Y_i$ in the following specification:

$$P_i = \alpha + \beta Y_i + \epsilon_i \quad (4.4)$$

In Equation 4.4, the residual term $\epsilon_i$ includes amenities, land scarcity, infrastructure, and other attributes of city $i$ that other than employment growth $Y_i$ affect the price of housing. In general, these attributes will not be uncorrelated with $Y_i$, and therefore the regressor $Y_i$ is endogenous. Formally, decomposing $\mathbb{E}[Y_i\epsilon_i]$ using the decomposition from Equation 4.3
yields the following potential sources of endogeneity:

\[ \mathbb{E}[Y_i e_i] = \mathbb{E}[u_i e_i] + \sum_j v_j \mathbb{E}[\kappa_{ij} e_i] + \sum_j \mathbb{E}[\kappa_{ij} \varepsilon_{ij} e_i] \] (4.5)

The correlation between city-specific employment growth component \( u_i \) and residual price component \( e_i \) is of immediate concern as a source of potential endogeneity bias. The Bartik shock instrument corrects the bias caused by this first term on the right-hand side of Equation 4.5. To see this, note that the Bartik shock as defined in Equation 4.2 can be rewritten as

\[ \frac{1}{I} \sum_{i \neq i} u_{-i} + \sum_j \kappa_{ij} v_j + \frac{1}{I} \sum_{i \neq i} \sum_j \kappa_{ij} \varepsilon_{-ij} \] for city \( i \). For \( I \to \infty \) and independent distribution of \( u_i, \kappa_i \), and \( \varepsilon_i \) across cities, this reduces to \( B_i = \sum_j \kappa_{ij} v_j \). Substituting this form for \( B_i \) and using the independence of observations across cities yields the following corresponding condition to Equation 4.5 for the Bartik shock:

\[ \mathbb{E}[B_i e_i] = \sum_j v_j \mathbb{E}[\kappa_{ij} e_i] \] (4.6)

The implicit identifying assumption in using the Bartik shock as an instrument is that \( \mathbb{E}[B_i e_i] = 0 \). Equation 4.6 shows that this is equivalent to assuming that \( \kappa_{ij} \) and \( e_i \) are uncorrelated. In other words, the Bartik shock instrumentation strategy assumes that, conditional on employment growth \( Y_i \), industrial composition \( \kappa_i \) is uncorrelated with the outcome variable of interest.

In many cases encountered in the literature, this assumption may be strong. For example, studies including Guerrieri, Hartley and Hurst (2013) and Partridge et al. (2012) have used Bartik shock instruments to study migration responses to labour demand shocks, but the response to national labour demand shocks is likely very different in cities where a single large industry dominates. Compared to a more diversified city, a decline in the dominant industry would limit a worker’s ability to adjust by finding a new job in the same city, and the worker may be more likely to perceive a risk of other employment prospects declining in the future. Duranton and Turner (2011) use the Bartik shock to instrument for demand for vehicle distance travelled, although the demand for shipping and commuting likely varies widely in cities with different industrial composition. As discussed in Davidoff
(2015), the use of Bartik shock instruments to estimate housing supply functions in Saiz (2010) implicitly assumes that industrial composition is uncorrelated with land scarcity, amenities, regulation, or other city attributes that would also affect prices. Similarly, in the Luttmer (2005) study of subjective well-being, the Bartik shock instrument implicitly requires industrial composition to be uncorrelated with local amenities or taste for regulation, as these local conditions likely enter into residents’ utility functions.

The assumption that $\sum_j v_j E[\kappa_{ij} e_i] = 0$ is untestable. However, it is possible to use the available information in the model to focus the correlation issue more narrowly. Define $\gamma = \frac{\text{Cov}(u_i, e_i)}{\text{Var}(u_i)}$, so that $e_i = \gamma u_i + \omega_i$ where $\omega_i$ by definition is the component of $e_i$ orthogonal to $u_i$. Then, impose the following identifying assumption on the uncorrelated component $\omega_i$:

**Assumption 1.** $\sum_j v_j E[\kappa_{ij} \omega_i] = 0$

Assumption 1 requires that the correlation with industrial composition in $e_i$ must be reflected in the city-specific component of industrial performance $u_i$. That is, it states that projecting $e_i$ onto $u_i$ removes the component of $e_i$ which is correlated with industrial composition. As with any identifying assumption, Assumption 1 cannot be directly tested in the data. To see this, note that the “true” values of $e_i$ and therefore $\omega_i$ are not observable.

The projection of $e_i$ onto $u_i$ accounts for some sources of potential endogeneity, but it is by no means universally applicable. Assumption 1 is likely defensible in situations where the primary exogeneity concern of the Bartik shock arises from the decline of a single large sector impacting workers’ decisions more than industry-weighted labour market performance would suggest. For many of the confounding local conditions in the Bartik shock framework (e.g., productivity spillovers, amenities, and taste for regulation), whether these conditions can be projected out onto the city-specific component $u_i$ of the employment growth is an empirical question.

Note that Assumption 1 is not a radical departure from the standard Bartik shock identifying assumption. As discussed previously, to justify the use of the Bartik shock as an instrumental variable, it is implicitly necessary to assume $E[B_t e_i] = 0$. Given the result of Equation 4.6, this is equivalent to assuming $\sum_j v_j E[\kappa_{ij} e_i] = 0$. Therefore, Assumption 1 in
some sense generalizes the standard Bartik assumption by placing restrictions only on the
$\omega_i$ component of $e_i$ which is orthogonal to $u_i$ (and therefore not accessible from observable
labour market outcomes) rather than on the entire $e_i$ term. In the special case $\gamma = 0$, the
approach based on Assumption 1 reduces to the standard Bartik instrument approach.

Assumption 1 yields potentially useful moment conditions in terms of $Y_i$. Expanding
$\mathbb{E}[Y_i \omega_i]$ analogously to Equation 4.5 yields the following expression:

$$
\mathbb{E}[Y_i \omega_i] = \mathbb{E}[u_i \omega_i] + \sum_j v_j \mathbb{E}[\kappa_{ij} \omega_i] + \sum_j \mathbb{E}[\kappa_{ij} \epsilon_{ij} \omega_i] \quad (4.7)
$$

Then, applying Assumption 1 and the fact that $\mathbb{E}[u_i \omega_i] = 0$ by definition yields the
following moment condition for $Y_i$:

$$
\mathbb{E}[Y_i \omega_i] = \sum_j \mathbb{E}[\kappa_{ij} \epsilon_{ij} \omega_i] \quad (4.8)
$$

Similarly, expanding $\mathbb{E}[Y_i \omega_i]$ and applying Assumption 1 yields the following moment
condition for $B_i$:

$$
\mathbb{E}[B_i \omega_i] = 0 \quad (4.9)
$$

The moment conditions specified by Equations 4.8 and 4.9 suggest a control function
approach to estimating the parameters of Equation 4.4 under Assumption 1. To implement
this, form estimates $\hat{u}_i$ of $u_i$ (as discussed in detail below) then estimate the following
equation:

$$
P_i = \alpha + \beta Y_i + \gamma \hat{u}_i + \omega_i \quad (4.10)
$$

The optimal approach to estimating Equation 4.10 depends on whether the remaining bias
term in Equation 4.8 is of concern. If this term (which involves the correlation between
industrial composition, the industry-city residual of labour market performance, and the $\omega_i$
residual component) is negligible, then Equation 4.10 can be estimated via OLS. However,
the moment condition specified by Equation 4.9 suggests that Equation 4.10 will also be con-
sistently estimated using the Bartik shock as an instrument. Accordingly, the novel control
function approach in this paper is complementary to the canonical Bartik instrumentation
strategy in terms of its ability to account for endogeneity.

It is worth emphasizing that this control function approach adds information to the regression compared to solely using the Bartik shock. To see this, compare a “first-stage” regression that decomposes $Y_i$ onto $B_i$ (plus an orthogonal error) with one that decomposes $Y_i$ onto $B_i$ plus $\hat{u}_i$ (plus an orthogonal error). These two decompositions are not equivalent; in general, $\hat{u}_i$ neither orthogonal nor collinear with $B_i$. (Specifically, $\text{Cov} (\hat{u}_i, B_i) = \frac{1}{J} \sum_j v_j \text{Cov} (u_i, \kappa_{ij}) + \frac{1}{J} \sum_j \sum_{j'} v_j \text{Cov} (\varepsilon_{ij'}, \kappa_{ij'}).$) Accordingly, the use of the $\hat{u}_i$ control function is not equivalent to regressing employment growth on the Bartik shock and then using the residual of this regression to form a control function.

Intuitively, the control function approach adds “flexibility” by allowing $u_i$ to enter both through $Y_i$ and through the residual. As made explicit by Assumption 1, if the residual $e_i$ can be projected on to $u_i$, then the control function approach addresses the endogeneity in the moment condition given by Equation 4.6 and replaces it with the moment condition given by Equation 4.9. Therefore, this yields an unbiased estimate for $\beta$.

It remains to obtain an estimate $\hat{u}_i$ for $u_i$. Unfortunately, it is only possible to $u_i$ to $O(\frac{1}{J})$. To see this, define the estimator $\hat{v}_{j;i}$ for each $i$ as $\hat{v}_{j;i} = \frac{1}{I-1} \sum_{i \neq j} y_{ij}$ (since $I$ is asymptotically large, this estimator is consistent). Then, define $\hat{u}_i$ as follows:

$$\hat{u}_i = \frac{1}{J} \sum_j (y_{ij} - \hat{v}_{j;i}) \quad (4.11)$$

Equation 4.11 uses the definition of $u_i$ as the city-level component of industrial performance to obtain an estimate. However, the bias in this estimate is $u_i - \hat{u}_i = \sum_j \varepsilon_{ij}$. Given that $E [\varepsilon_{ij}] = 0$, this term would decrease to zero as $J \rightarrow \infty$. Since $J$ is finite, the bias term for a given city $i$ is in general nonzero. Rather, it will decrease in magnitude as $J$ increases at a rate proportional to $\frac{1}{J}$. This issue is comparable to the bias that arises from too many regressors in a classical linear regression model; effectively, the number of parameters $\hat{u}_i$ is increasing proportionally to the sample size. However, for sufficiently disaggregated industries $J$, this represents an arbitrarily close estimate. Moreover, correlation from $\varepsilon_{ij}$ is generally a secondary concern compared with correlation from $u_i$ terms.
4.3 Empirical results

To demonstrate the use of the control function approach introduced above, I estimate the housing supply function specified by Equation 4.4. In using the control function approach, I assume that Assumption 1 holds. For this assumption to be valid, all factors in residual term $e_i$ (which contains all aspects of housing prices uncorrelated with $Y_i$) would have to either lie parallel to $u_i$ or be uncorrelated with industrial composition. This is an identifying assumption which cannot be directly tested. However, this demonstration represents a situation where a researcher could conceivably be concerned with the Bartik shock’s correlation with industrial composition and where assuming that the undesirably correlation could be projected out along $u_i$ is a potentially reasonably assumption.

I consider four specifications:

1. OLS estimation without accounting for $u_i$ terms. The moment conditions for this specification are equivalent to assuming the right-hand side of Equation 4.5 is zero.

2. IV estimation using the Bartik shock to instrument for city-level employment growth (the classic Bartik approach). As discussed previously, this requires the assumption that right-hand side of Equation 4.6 is zero.

3. OLS estimation using a control function approach to account for $u_i$. This is equivalent to Assumption 1 combined with the assumption that the right-hand side of Equation 4.8 is zero.

4. IV estimation using the Bartik shock with a control function approach to account for $u_i$. This is equivalent to Assumption 1.

I estimate this model using 2000 and 2010 Census and FHFA House Price Index data. To ensure consistency and comparability, I use consistent Public Use Microdata Area boundaries mapped to consistent boundaries and consistent 1990 industry classifications. I focus on the broadest category of industrial sectors, such as “manufacturing” and “retail trade” ($J = 13$) and delineate cities using the metropolitan statistical area and metropolitan divisions in the FHFA data ($I = 398$). Following the literature, I only include civilian
workers between the ages of 25 and 55 who work at least 35 hours per week. I only consider metropolitan statistical areas or metropolitan divisions with at least 25,000 workers in these categories in 2000. I calculate \( \hat{v}_j \) with cities weighted by population. This follows the literature and gives stable estimates.

Table 4.1 shows the results of these estimations. As shown, the OLS regressions predict much smaller price responses to employment than the IV regressions. The estimates for \( \gamma \) are small but positive, which indicates that a local labour market that outperforms its industry-weighted average predicted performance is likely to have a positive house price premium. The coefficient \( \gamma \) is statistically significant at \( p < 0.05 \) in the OLS case, but not in the IV case.

The addition of the control function modestly increases the estimated magnitude of the price response in both the OLS and IV regressions. However, the impact of the control function adjustment is much smaller than the impact of the Bartik shock adjustment. The small impact of the control function is likely driven by the relatively small estimate for \( \gamma \), which indicates that, if Assumption 1 is valid, the correlation between \( u_i \) and the first-stage error \( e_i \) is not particularly strong in this context. Accordingly, projecting \( e_i \) along \( u_i \) does not remove much of the variation in \( e_i \).

If the magnitude of \( \gamma \) were higher and Assumption 1 holds then the difference between the IV estimates with and without the control function would be much larger. Under Assumption 1 the bias in the IV estimate without the control function (relative to the value with the control function) is given by

\[
\frac{\sum_j v_j E[u_i | v_j]}{\text{Cov}(Y_i, B_i)}.
\]

Estimating \( \frac{\sum_j v_j E[u_i | v_j]}{\text{Cov}(Y_i, B_i)} \) from the...

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<th>IV Control</th>
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Table 4.1: Regression results for the housing supply curve at the MSA level. For legibility, the control function coefficient and its standard errors are scaled by a factor of 10^3. Standard errors in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%.
data gives a value of -53.8, which is substantial on the scale of the estimated parameters. Therefore, conditional on Assumption 1 holding, the small difference between the Bartik shock IV estimates with and without the control function does not indicate that correlation between the residual term \(e_i\) and the industrial composition \(\kappa_i\) should not be of concern as a source of endogeneity bias. Rather, it indicates that the control function approach cannot account for a substantial share of \(e_i\) because \(\gamma\) is relatively low in magnitude.

The large difference between the instrumented and uninstrumented regressions compared with the smaller difference between controlled and uncontrolled regressions has two possible explanations. The first possibility is that the similar differentials between OLS and IV estimates with and without the control function suggests that the rightmost term in Equation 4.5 and the right-hand side term of Equation 4.8 are responsible for most of the endogeneity bias. That is, the Bartik shock improves estimates not by addressing substantial endogeneity not only from \(E[u_i e_i]\) terms but also from \(E[\kappa_{ij} \varepsilon_{ij} e_i]\) or \(E[\kappa_{ij} \varepsilon_{ij} \omega_i]\) terms. Note that this scenario is possible regardless of whether Assumption 1 holds as Assumption 1 does not affect the \(\varepsilon_{ij}\) terms. However, under this scenario, if Assumption 1 did hold, this would mean that \(\sum_j v_j E[\kappa_{ij} \omega_i] = 0\) but \(\sum_j E[\kappa_{ij} \varepsilon_{ij} \omega_i] \neq 0\) — that is, the correlation between the \(\kappa_{ij}\) industrial share terms and the \(\omega_i\) terms would need to be acting through the \(\varepsilon_{ij}\) terms. These could potentially be the case if, for example, city-specific idiosyncratic growth in high-tech industries or decline in manufacturing only affects housing prices if the industry is already particularly large in that city. In this situation, the estimation using both the Bartik shock instrument and the control function yields unbiased estimates.

The other possibility is that the estimates for \(\hat{u}_i\) are particularly noisy — that is, if the bias from the \(\varepsilon_{ij}\) terms is substantial. In this case, \(\hat{u}_i\) would be less effective at projecting out the component of \(e_i\) parallel to \(u_i\), and therefore the additional information from adding the \(\hat{u}_i\) (to either the instrumented or uninstrumented regression) would be limited. This situation is consistent with the very low estimates for the coefficient \(\gamma\). Moreover, this possibility seems feasible from the data, as the outliers in the set of calculated values for \(\hat{u}_i\) are very disperse. Note that it is not possible to recover the “true” values for \(u_i\) and therefore not possible to assess whether the \(\hat{u}_i\) values closely represent the underlying \(u_i\).

Increasing \(J\) to 34 by subdividing the manufacturing and the transportation, commu-
nication, and public utilities sectors does not substantially reduce the incidence of the very extreme outlying estimated values for $\hat{u}_i$. This may be because finer industries can have larger idiosyncratic city-industry shock terms $\varepsilon_{ij}$.

### 4.4 Conclusion

Bartik shocks are widely used as an instrument for local aggregate demand. They are highly predictive, but other researchers in the literature have expressed concerns that effects arising from differences in industrial composition may influence the instrument’s predictive power and complicate its interpretation as exogenous. This study introduces a control function approach to estimation. The control function approach requires an additional identifying assumption. As with any identifying assumption, the validity of Assumption 1 cannot be tested but must be argued as plausibly valid for a given empirical application. In some situations, the control function described here may offer a more plausible source of variation than the Bartik shock. Moreover, the control function estimation outlined in this study may be used in conjunction with the Bartik shock instrument.

I demonstrate the use of this control function approach in estimating a housing supply curve. My results suggest that in the context of this particular application the control function has minimal impact. The small impact of the control function relative to the Bartik instrument may suggest that endogeneity is driven by idiosyncratic city-industry specific shocks. Alternately, it may suggest that the estimation strategy outlined above to estimate $\hat{u}_i$ does not provide a close estimate to $u_i$ given the finite value of $J$. 

5 Conclusion

This thesis consists of three empirical studies in economics. In the first, I estimate a model of nightlife industry dynamics to uncover profit spillovers between closely related industries. In the second, my coauthor and I introduce a new measure of urban structure and show that it has substantial impact on housing price dynamics. In the third, I introduce a potential improvement to an econometric technique that is widely used in urban economics. Taken together, this work constitutes a significant contribution to the body of economic knowledge.

Each of the three studies in this thesis offer a novel contribution to the economic literature. “Industry dynamics and the value of variety in nightlife: evidence from Chicago” estimates a structural dynamic model of nightlife venue entry and exit and finds evidence of positive profit spillovers both within and between types of venue. “Land value gradients and the level and growth of housing prices” introduces a new measure of willingness to substitute between neighbourhoods and shows that this new measure has a close relationship with cross-city differences in housing prices. “A control function approach to the correlated components of Bartik shocks” introduces a new estimation technique that in some situations may improve upon the existing widely-used Bartik shock methodology.

It is also worth discussing the limitations of these papers. In particular, due to the short timeframe of the available data relative to the scale of neighbourhood change “Industry dynamics and the value of variety in nightlife: evidence from Chicago” relies on a structural framework in which firms are forward-looking regarding each others’ behaviour but consumers cannot choose to relocate. While it performs well compared to other measures in the literature, the new gradient measure introduced in “Land value gradients and the level and growth of housing prices” cannot explain away the higher housing price levels and growth in coastal cities. The estimation of the control function described in “A control function approach to the correlated components of Bartik shocks” may not yield a sufficiently close approximation to the “true” underlying control function in realistic data sets. Each of these issues suggest directions for continued investigation.
In addition to the relevance of the empirical results and novel methods to the academic literature, several elements of this thesis are also useful in the context of urban policy and planning. As discussed previously, nightlife is an active focus of policy concern in a broad range of cities. “Industry dynamics and the value of variety in nightlife: evidence from Chicago” directly tests the impacts of local zoning policies and other policies which pose barriers to entry for nightlife venues. As well, “Land value gradients and the level and growth of housing prices” provides useful results for policymakers seeking to understand cross-sectional differences housing market dynamics and their implications for housing affordability and macroprudential housing cycle regulation.

Each of these studies indicates future directions of research. In particular, I plan to expand on the model developed in “Industry dynamics and the value of variety in nightlife” using richer data sets to understand how firms in other retail industries (such as the restaurant industry) differentiate themselves in location and characteristics. This research could substantially contribute to the understanding of how people interact with the cities they inhabit and how firms respond to that behaviour. As well, I plan to build on the results in the other papers to understand the origins and dynamics of cities’ rent gradients and to develop new estimation techniques that provide plausibly exogenous variation to labour demand. These improvements would be useful to urban economists seeking to understand how cities grow and develop over time.
Bibliography


Byrne, John. 2012. “Voters will have say on whether Chicago’s Galewood precinct goes dry.” Chicago Tribune.


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Appendices

A Proof of Proposition 1

This appendix provides a proof for Proposition 1, which guarantees the existence of a unique set of equilibrium prices for the static model outlined above. It builds on the proof provided in Kucheryavyy (2012). I extend this result to account for venues’ response to consumers’ reservation utility.

This proof only applies for the case where \( n_\ell > 0 \) for all venue types \( \ell \). In \( n_\ell = 0 \) for some type, then no well-defined equilibrium price exists. However, upon removing the type \( \ell \) with \( n_\ell = 0 \) from consideration, the proof does hold for the remaining types.

For clarity, I focus on the case where \( N < \bar{N} \) — that is, where \( V(p) < 1 \) and therefore some consumers are opting not to go out and instead to consume their reservation utility. The proof for the case where \( N \geq \bar{N} \) follows the same rationale but with less complexity.

First, I prove the uniqueness of the vector of prices. Equation 2.6 gives prices \( p_\ell i \) as a function of the market shares \( S_\ell \):

\[
p_{\ell i} = \left(1 + \frac{n_\ell}{n_\ell (\rho_\ell - 1) - \left(\rho_\ell - \left[1 + S_\ell^{\frac{n}{n-1}} \sum_{\ell'} \left(S_{\ell'}^{\frac{n}{n-1}} \right)^{-1}\eta\right] - 2(\eta - 1) S_\ell\right)}\right) c_\ell
\]  

Note that Equation 2.2 suggests that the share of consumption to sector \( \ell \) \( S_\ell \) can be written in terms of the price index \( P_\ell \) as follows:

\[
S_\ell = \frac{P_\ell^{1-\eta}}{\sum_{\ell'} P_{\ell'}^{1-\eta}}
\]  

For symmetric venues, \( P_\ell = n^{1-\rho_\ell} p_{\ell i} \). Substituting \( p_{\ell i} \) gives the following fixed-point
equation for $S_\ell$:

$$
S_\ell = \frac{1-n}{n_\ell^{1-\rho_\ell}} \left( 1 + \frac{n_\ell}{n_\ell(\rho_\ell-1)-\left(\rho_\ell-1+S_\ell^{\eta-1} \sum_{\ell'} \left(S_{\ell'}^{\eta-1}\right)^{-1}\right)-2(\eta-1)S_\ell} \right)^{1-\eta} \left( 1 + \frac{n_{\ell'}^{1-\rho_{\ell'}}}{n_{\ell'}(\rho_{\ell'}-1)-\left(\rho_{\ell'}-1+S_{\ell'}^{\eta-1} \sum_{\ell''} \left(S_{\ell''}^{\eta-1}\right)^{-1}\right)-2(\eta-1)S_{\ell'}} \right)^{1-\eta}
$$

(3)

This defines a system of $L$ equations for the shares $S_\ell$ which map the hypercube $[0, 1]^L$ into itself\(^1\). As this is a continuous mapping of a closed set into itself, Brouwer’s fixed point theorem applies. Therefore, an equilibrium $S_\ell$ must exist.

Next, note that this equilibrium must be unique. To see this, note that the left-hand side of Equation 3 is strictly increasing and continuous in $S_\ell$ while the right-hand side is strictly decreasing and continuous. Therefore, they must intersect at most once. Because Brouwer’s fixed point theorem guarantees that they intersect at least once, it must be that they intersect exactly once. Therefore, there exists a unique equilibrium set of shares $S_\ell$.

Substituting into 2.2 gives a corresponding unique equilibrium set of prices.

This completes the proof. While the exposition has focused on the case where $V(p) < 1$, a directly analogous proof holds for $V(p) \geq 1$. In this case, the expression for the fixed-point equation for $S_\ell$ (the equivalent of Equation 3) is as follows:

$$
S_\ell = \frac{1-n}{n_\ell^{1-\rho_\ell}} \left( 1 + \frac{n_\ell}{n_\ell(\rho_\ell-1)-\left(\rho_\ell-1+S_\ell^{\eta-1} \sum_{\ell'} \left(S_{\ell'}^{\eta-1}\right)^{-1}\right)-2(\eta-1)S_\ell} \right)^{1-\eta} \left( 1 + \frac{n_{\ell'}^{1-\rho_{\ell'}}}{n_{\ell'}(\rho_{\ell'}-1)-\left(\rho_{\ell'}-1+S_{\ell'}^{\eta-1} \sum_{\ell''} \left(S_{\ell''}^{\eta-1}\right)^{-1}\right)-2(\eta-1)S_{\ell'}} \right)^{1-\eta}
$$

(4)

It remains to show that either the case $V(p) < 1$ or the case $V(p) \geq 1$ yields consistent results. That is, it remains to show that either when venues follow the pricing strategy specified by the first option in Equation 2.6 the value to consumers of going out is less than 1 or when venues follow the pricing strategy specified by the second option in Equation 2.6 the value to consumers of going out is greater than 1. That is, let $p^{\text{non}}$ be the vector of

\(^1\)Strictly speaking, Equation 3 defines a mapping on the set $[0, 1]^L \setminus \{0\}$ as the term $S_\ell^{\eta-1} \sum_{\ell'} \left(S_{\ell'}^{\eta-1}\right)^{-1}$ is not defined when all shares $S_\ell$ are identically zero. However, this singularity is removable; setting this term to one when all shares are zero yields a continuous function.
venue prices given by the first-order condition for the case \( V(p) < 1 \) and \( p_{\text{max}} \) be the vector of venue prices given by the first-order condition for the case \( V(p) \geq 1 \). Then, it remains to show that in all situations either \( V(p_{\text{non}}) < 1 \) or \( V(p_{\text{max}}) \geq 1 \).

I prove this by showing \( p_{\text{max}} \leq p_{\text{non}} \). Then, according to Equation 2.3, \( V(p_{\text{non}}) \leq V(p_{\text{max}}) \). From here, the desired consistency result follows immediately. To show this, rearrange Equation 2.6 as follows:

\[
\left( \frac{p_{\ell i}^{\text{non}}}{c_{\ell}} - 1 \right)^{-1} = \left( \frac{p_{\ell i}^{\text{max}}}{c_{\ell}} - 1 \right)^{-1} + \eta S_{\ell}^{\eta - 1} \left( \sum_{\ell'} S_{\ell'}^{\eta - 1} \right)^{-1} - (\eta - 1) S_{\ell} \quad (5)
\]

From here, it is sufficient to show \( \eta S_{\ell}^{\eta - 1} \left( \sum_{\ell'} S_{\ell'}^{\eta - 1} \right)^{-1} - (\eta - 1) S_{\ell} \geq 0 \) for all possible \( S_{\ell} \). Note that this is guaranteed to hold for \( S_{\ell} = 0 \) and for \( S_{\ell} = 1 \). It remains to show that it holds for the interior critical point. Taking the first-order condition and rearranging yields a minimum when \( \eta S_{\ell}^{\eta - 1} \left( \sum_{\ell'} S_{\ell'}^{\eta - 1} \right)^{-1} - (\eta - 1) S_{\ell} \geq 0 \). However, at this value of \( S_{\ell} \), the necessary condition holds whenever \( S_{\ell}^{\eta - 1} > \eta - 1 \), which is satisfied whenever \( \eta > 2 \). Therefore, \( p_{\text{max}} \leq p_{\text{non}} \). This completes the proof.

It is worth discussing the intuition for the requirement \( \eta > 2 \). In the case \( \eta \leq 2 \), consumers are very sensitive to variety between venues. In this case, depending on parameter values, it is possible that an individual venue in the \( V(p) < 1 \) case may lower prices below \( p_{\text{max}} \) to entice more consumers to come out. In this case, there is no guarantee that either pricing strategy will be consistent with the consumers’ indirect utility. However, empirically it does appear that \( \eta > 2 \).

Note that in some cases multiple equilibria are possible — that is, it is possible for a neighbourhood to be in a state such that setting a price vector \( p_{\text{non}} \) according to the \( V(p) < 1 \) case gives \( V(p_{\text{non}}) < 1 \) but also setting a price vector \( p_{\text{max}} \) according to the \( V(p) \geq 1 \) case gives \( V(p) \geq 1 \). When this occurs, I assume that the venues set prices according to \( p_{\text{non}} \). Not only would any unilateral deviation to \( p_{\text{max}} \) result in lower profits, but also as a practical consideration using the \( p_{\text{non}} \) case whenever it is consistent leads to fewer “jumps” in profit as a function of parameters and therefore more tractable estimation. Numerical simulation suggests that when multiple equilibria arise they are both very close
to $V = 1$ with similar prices to each other.
B Proof of Proposition 2

This appendix provides a proof of Proposition 2, which states that with sufficiently many venues the equilibrium prices give \( V(p) \geq 1 \) — that is, with sufficiently many venues, nightlife is sufficiently vibrant that all consumers choose to go out. To prove this result, I show that with sufficiently many venues the optimal price vector \( p^{non} \) based on the optimal pricing strategy for the case \( V(p) < 1 \) yields \( V(p^{non}) > 1 \). Since Proposition 1 shows that \( V(p^{non}) < V(p^{max}) \) (i.e., the optimal pricing strategy when \( V(p) < 1 \) always gives a lower utility than the optimal pricing strategy when \( V(p) \geq 1 \)), the desired result follows immediately.

First, rewrite the indirect utility from Equation 2.3 entirely in terms of the venues’ prices \( p_{\ell i} \):

\[
V(p) = w \sum_{\ell} n^{\rho_{\ell i}^{-1}} p_{\ell i}^{-\eta} \left( \sum_{\ell} n^{\rho_{\ell i}^{-1}} p_{\ell i}^{-1-\eta} \right)^{-1} \tag{6}
\]

From here, it remains to show that for all \( \ell \in 1, 2, \ldots, L \), \( n^{\rho_{\ell i}^{-1}} p_{\ell i}^{-\eta} \) grows faster in \( n_{\ell} \) than \( n^{\rho_{\ell i}^{-1}} p_{\ell i}^{-1-\eta} \) when \( p = p^{non} \). This will provide the necessary result, since it indicates that the value of going out under the \( V(p) < 1 \) pricing strategy increases indefinitely with \( n_{\ell} \).

Note that in Equation 2.6 the price for the case \( V(p) < 1 \) (expressed in big-O notation in \( n_{\ell} \)) is \( O(1) \). Specifically, as \( n_{\ell} \) increases, the optimal price for the case \( V(p) < 1 \) approaches the constant markup price \( p_{\ell i} = \frac{p_{\ell i}^{c} + 1}{p_{\ell i}^{c}} c_{\ell} \). Accordingly, \( n^{\rho_{\ell i}^{-1}} p_{\ell i}^{-\eta} \) is \( O \left( n^{\rho_{\ell i}^{-1}} \right) \) while \( n^{\rho_{\ell i}^{-1}} p_{\ell i}^{-1-\eta} \) is \( O \left( n^{\rho_{\ell i}^{-1}} \right) \). As \( \frac{\eta}{\rho_{\ell i}^{-1}} > \frac{\eta - 1}{\rho_{\ell i}^{-1}} \), the numerator term grows faster with \( n_{\ell} \) than the denominator term. Therefore, the overall indirect utility under the \( V(p) < 1 \) prices must eventually exceed 1 for sufficiently large \( n_{\ell} \). This completes the proof.
C Venue category verification

To ensure that these venue types inferred from the liquor licensing data set correspond to real-world qualitative categories of venues, I match the venues to Yelp listings. I search for each venue by latitude and longitude using the Yelp API and then match business names in the licensing data to business names on Yelp using pattern matching. The pattern matching algorithm does not require an exact match. For example, I match the venue “Checker Board Lounge” from the business license data with the Yelp listing “Checkerboard Lounge” and the venue “Six Penny B P” from the business license data with the Yelp listing “Six Penny Bit”. Yelp assigns categories to businesses, such as “Buffets” or “Sports Bars” or “Massage”. An individual business may be assigned multiple categories. The Yelp API does not return all businesses which have already closed and I am unable to match businesses which operate under substantially different names than their names in the license data. Accordingly, I can identify only 19% of the businesses on Yelp.

I use a multinomial logit regression to examine how closely the Yelp categories and liquor licensing categories coincide. I regress the liquor licensing categories on indicator variables for whether Yelp assigned the venues to the six most commonly-assigned Yelp categories in the sample: “Dance Clubs”, “Pubs”, “Lounges”, “Music Venues”, “Sports Bars”, and “Bars”. Table C1 shows the results of this regression. As shown, the Yelp categories are generally significant predictors of the liquor licensing categories. In particular, many of the coefficients are large in magnitude and significantly different from zero, venues which Yelp assigns to the “Dance Club” category are much less likely to be in the “Drinks only” license category, and venues which Yelp identifies as “Pubs” are much less likely to be in the “Drinks and amusement” license category. Therefore, the comparison with Yelp suggests that the categories based on business licenses constitute a reasonable division of the venues into categories that would be relevant to consumers.
Table C1: Results of a multinomial logit regression of the licensing categories on the most frequently-assigned Yelp categories. The regression sample is the set of venues which matched with Yelp businesses. The omitted licensing category is the “Amusement only” category. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

<table>
<thead>
<tr>
<th></th>
<th>Drinks only</th>
<th>Drinks and amusement</th>
<th>Drinks and music</th>
</tr>
</thead>
<tbody>
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<td>Intercept</td>
<td>0.993**</td>
<td>−1.474**</td>
<td>−0.998*</td>
</tr>
<tr>
<td></td>
<td>(0.404)</td>
<td>(0.665)</td>
<td>(0.601)</td>
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<td>Dance Clubs</td>
<td>−0.273</td>
<td>2.485**</td>
<td>2.096*</td>
</tr>
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<td></td>
<td>(1.207)</td>
<td>(1.226)</td>
<td>(1.223)</td>
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<td>Pubs</td>
<td>16.864***</td>
<td>0.742***</td>
<td>16.997***</td>
</tr>
<tr>
<td></td>
<td>(0.357)</td>
<td>(0.000)</td>
<td>(0.357)</td>
</tr>
<tr>
<td>Lounges</td>
<td>2.297**</td>
<td>2.947**</td>
<td>2.222*</td>
</tr>
<tr>
<td></td>
<td>(1.086)</td>
<td>(1.217)</td>
<td>(1.220)</td>
</tr>
<tr>
<td>Music Venues</td>
<td>−0.053</td>
<td>1.742</td>
<td>0.570</td>
</tr>
<tr>
<td></td>
<td>(1.185)</td>
<td>(1.262)</td>
<td>(1.355)</td>
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<td>Sports Bars</td>
<td>17.685***</td>
<td>17.387***</td>
<td>17.256***</td>
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<tr>
<td></td>
<td>(0.444)</td>
<td>(0.644)</td>
<td>(0.612)</td>
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<td>Bars</td>
<td>18.471***</td>
<td>18.375***</td>
<td>17.678***</td>
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<td>(0.361)</td>
<td>(0.477)</td>
<td>(0.485)</td>
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<td>−141.689</td>
<td>−141.689</td>
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<td>283.379</td>
<td>283.379</td>
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D Maximum likelihood estimation results

Table D1 shows the full set of parameter results from the maximum likelihood estimation, including not only the parameter values discussed above but also the parameters relating neighbourhood attributes to the profit function. Equations 2.16 and 2.17 define how the estimated parameters relate to the model quantities.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Estimate</th>
</tr>
</thead>
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<tr>
<td>Elasticity between sectors</td>
<td>$\eta$</td>
<td>$2.04 \pm 0.000162$</td>
</tr>
<tr>
<td>Elasticity within sector Amusement only</td>
<td>$\rho_1$</td>
<td>$4.90 \pm 0.000131$</td>
</tr>
<tr>
<td>Elasticity within sector Drinks only</td>
<td>$\rho_2$</td>
<td>$2.15 \pm 0.00086$</td>
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<tr>
<td>Elasticity within sector Drinks and amusement</td>
<td>$\rho_3$</td>
<td>$3.56 \pm 0.00224$</td>
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<tr>
<td>Elasticity within sector Drinks and music</td>
<td>$\rho_4$</td>
<td>$7.96 \pm 0.00029$</td>
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<tr>
<td>Marginal cost Drinks and amusement</td>
<td>$c_3$</td>
<td>$3.85 \pm 0.00269$</td>
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<td>$c_4$</td>
<td>$2.54 \pm 0.000662$</td>
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</tr>
<tr>
<td>Entry arrival rate Drinks only</td>
<td>$\alpha_2$</td>
<td>$9.05 \times 10^{-1} \pm 9.76 \times 10^{-2}$</td>
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<td>Entry arrival rate Drinks and amusement</td>
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<td>$1.48 \times 10^{-2} \pm 2.43 \times 10^{-2}$</td>
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<td>Symbol</td>
<td>Estimate</td>
</tr>
<tr>
<td>-----------------------------------------</td>
<td>--------</td>
<td>----------------</td>
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</table>
| Exit arrival rate Amusement only        | $\lambda_1$ | $5.08 \times 10^{-3}$  
                    |         | $(1.07 \times 10^{-10})$ |
| Exit arrival rate Drinks only           | $\lambda_2$ | $9.03 \times 10^{-3}$  
                    |         | $(4.51 \times 10^{-6})$ |
| Exit arrival rate Drinks and amusement  | $\lambda_3$ | $2.31 \times 10^{-3}$  
                    |         | $(1.39 \times 10^{-5})$ |
| Exit arrival rate Drinks and music      | $\lambda_4$ | $2.10 \times 10^{-3}$  
                    |         | $(3.62 \times 10^{-8})$ |
| Log baseline entry cost Amusement only  | $\theta_{\psi_{\ell_1}}$ | 2.11  
                    |         | $(2.97 \times 10^{-3})$ |
| Log baseline entry cost Drinks only     | $\theta_{\psi_{\ell_2}}$ | 2.17  
                    |         | $(8.33 \times 10^{-3})$ |
| Log baseline entry cost Drinks and amusement | $\theta_{\psi_{\ell_3}}$ | 2.11  
                    |         | $(1.13 \times 10^{-2})$ |
| Log baseline entry cost Drinks and music | $\theta_{\psi_{\ell_4}}$ | 1.81  
                    |         | $(2.52 \times 10^{-1})$ |
| Log exit payoff Amusement only          | $\psi_1^x$ | -4.01  
                    |         | $(8.22 \times 10^{-1})$ |
| Log exit payoff Drinks only             | $\psi_2^x$ | -4.06  
                    |         | $(6.25 \times 10^{-2})$ |
| Log exit payoff Drinks and amusement    | $\psi_3^x$ | -2.76  
                    |         | $(3.24 \times 10^{-1})$ |
| Log exit payoff Drinks and music        | $\psi_4^x$ | -3.23  
<pre><code>                |         | $(7.07 \times 10^{-2})$ |
</code></pre>
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<thead>
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<th>Symbol</th>
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<td>Log entry cost</td>
<td>Dry precincts</td>
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<td>Moratoria</td>
<td>$\theta_{\psi_{r2}}$</td>
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<td></td>
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<td></td>
<td>Drinks and music</td>
<td>$\theta_{\kappa_{f4}}$</td>
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<tr>
<td>Log entrants</td>
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</tr>
<tr>
<td></td>
<td>Drinks only</td>
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<td>Log budget</td>
<td>$w$</td>
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117
<table>
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<tr>
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<td>Fixed cost parameter Principal component 4</td>
<td>$\theta_{cd4}$</td>
<td>$1.12 \times 10^{-4}$</td>
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<td>Market size Principal component 4</td>
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</table>

Table D1: Maximum likelihood estimation results for all parameters. If the variable name includes “Log”, I estimate the logarithm of the corresponding model parameter. Standard errors in parentheses.